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**Misspecification of Longitudinal Measurement Invariance Within the
Latent Transition Analysis Framework**

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Latent Transition Analysis Framework**

by

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Abstract

Misspecification of Longitudinal Measurement Invariance Within the Latent Transition Analysis Framework

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Assessing the impact of violations to longitudinal measurement invariance (LMI) within a mixture modeling context is not well-covered territory in current methodological research, and is notably unexplored in latent transition analyses (LTA). At a minimum, it can be assumed that any substantial departure from LMI within the LTA framework would thwart unambiguous interpretations of the latent classes as well as the probabilities of transitioning in and out of each latent class over time. The intent of this dissertation is to initiate the conversation by providing some thoughts and examples of how LMI can manifest in LTA models, followed by a statistical assessment of the most straightforward violation to LMI in LTA: configural non-invariance, or unequal numbers of latent classes emerging at each time point in the population.

Monte Carlo simulation methods were used to generate data exhibiting varying degrees of departure from configural LMI, then class enumeration decisions and

parameter recovery were explored under LTA models that assume configural invariance. The conditions manipulated in this simulation include the pattern of non-invariance (i.e., classes merging or splitting over time), class homogeneity and separation, class prevalence splits in the non-invariant class, overall sample size, and the transition matrix design (i.e., ordered or unordered movement).

By imposing a configurally invariant LTA model on data that are non-invariant in nature, the researcher is risking a complete misestimation of the number and type of latent classes that exist at a particular time point, particularly in terms of both under- and overestimated values of within-class agreement. For this reason, it is recommended that researchers make class enumeration decisions at each measurement occasion, based on time-specific latent class analyses (LCA), before fitting the overall LTA model to the data. Any non-invariance discovered at the LCA level can be substantively explored and modeled with a non-symmetrical LTA.

However, if the best-fitting class solution must be made at the LTA level, results from this study suggest that the AIC and ABIC indices are preferable for their overfitting tendencies. It seems reasonable to prefer an overfitted lens for analyzing non-invariant data, due to the added flexibility of the additional parameters estimated, but the parsimony of an underfitted model may be preferable in certain situations. As per usual, larger sample sizes (in this study, $N = 1,000$) are protective against parameter bias and convergence issues.

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Chapter 1: Introduction

The use of person-centered statistical modeling approaches, including finite mixture modeling, has been on the rise in educational and social science research over the last few decades, as attempts to categorize study participants into distinct homogenous subgroups may be substantively preferable to fitting a universal structure that is assumed to hold for all individuals. Latent class models extend from the latent variable modeling framework, where an unobserved factor (i.e., construct) is measured indirectly by multiple observed variables. In latent class analysis (LCA), the indirectly measured construct is categorical in nature, representing mutually exclusive and exhaustive subgroups of individuals who exhibit similar response patterns on the observed indicator items. For example, this methodological technique has been used to disentangle survey respondents into classes of varying levels of substance use during adolescence (Jackson & Schulenberg, 2013), disordered eating attitudes and behaviors (Bulik et al., 2000), and social phobias (Kessler et al., 1998).

The concepts behind latent class models can be applied to longitudinal data, as well. Latent growth models (LGM) explore homogenous subgroups of respondents over time by allowing for the estimation of multiple, class-specific growth parameters (e.g., intercept, slope factors). Another longitudinal adaptation of mixture modeling is the latent transition analysis (LTA). Borrowing from an autoregressive framework, LTA models estimate the probability of movement between distinct latent classes across two or more measurement occasions. In a typical application of the LTA model, the probability

of belonging to a latent class at one measurement occasion is regressed on class membership probabilities at the previous measurement occasion, thereby producing a matrix of transition probability parameters. Other parameters estimated by LTA models include within-class item response probabilities and class prevalence parameters. The LTA modeling framework allows for the flexible exploration of varying movement-related hypotheses (e.g., directional growth, specific growth patterns), as well as modeling extensions such as multigroup analysis and the addition of time-varying and/or time-invariant covariates.

As with any analysis of a measurement construct across time, regardless of methodological sophistication, the assumption of equivalent measurement properties at each time point is a critical prerequisite to growth-related hypothesis testing. Without the security of knowing that longitudinal measurement invariance (LMI) holds for observed or unobserved (i.e., latent) constructs, a researcher's conclusions about growth in that construct are spurious, at best. Does a model's estimation of growth suggest a true shift in the underlying construct? Or could it potentially reflect changes in participants' operational definition of the construct over time?

To aid the applied researcher in their quest for the security of LMI, several robust and familiar methods for assessing across-group (i.e., cross-sectional) measurement invariance have been tailored to the longitudinal modeling framework and are readily available to use in LTA models. A typical assessment of measurement invariance involves comparing model fit indices across nested models with and without equality constraints on the item-specific parameter(s) of interest. As there are several different

types of item-specific parameters estimated by the various methods for handling longitudinal data, there are accordingly several degrees of LMI that can be present in these estimating models. For example, configural, structural, distributional, and dispersional invariance levels have been proposed for both cross-sectional and longitudinal latent profile/class models (Morin et al., 2016), which sequentially vary in terms of equality constraints applied to model parameters.

If any degree of LMI has been detected in an applied setting, does that mean the team must abandon all hope of using longitudinal analysis techniques? Results from Monte Carlo simulation studies have been instrumental in providing applied researchers with evidence of their chosen model's robustness when exposed to particularly troublesome data that violate one or more underlying model assumptions. By simulating varying degrees of these violations, amongst other key model characteristics, Monte Carlo studies are able to design different data "truths" that are hopefully recaptured in estimation. Many of these studies explore outcomes such as parameter recovery (i.e., bias) and variability, convergence rates, statistical power, and Type I error rates. In doing so, they provide examples of which manipulated factors (or combination of factors) have a substantial impact on pertinent model results and subsequent interpretation. In other words, they are useful resources for providing applied researchers with a measure of confidence they can safely attribute to their analyses.

To date, very little methodological research has looked into the impact of varying degrees of longitudinal non-invariance in the mixture modeling framework, though Monte Carlo studies regarding across-group measurement invariance are plentiful. As

expected, results from the current limited research into LMI in latent growth modeling suggest that increasing departures from LMI have serious impacts on the model's growth parameters, specifically. However, there is no existing literature to help the LTA user understand how their specific model performs under threats to LMI.

The goal of this dissertation is to start filling in this gap in methodological research, and to initiate discussion on furthering the field's understanding of the multitude of ways longitudinal non-invariance can manifest from within the LTA framework. This is a broad and multifaceted endeavor, and obviously cannot be wholly tackled within a singular dissertation; however, small steps can be taken to advance the conversation and guide future research. The subsequent chapter provides an in-depth introduction to the LTA modeling framework and concepts of LMI, as well as a review of existing Monte Carlo studies on the impact of departures from LMI. Chapter 3 introduces the design behind the Monte Carlo simulation study that explores the impact of misspecifying LMI on the LTA model's parameter recovery, convergence rates, and class enumeration decisions. Results from the simulation study are presented and discussed in Chapter 4, and a brief summary of the entire study follows in Chapter 5. The reader is directed to several technical appendices to view the results through a finer lens.

Chapter 2: Literature Review

Often researchers in the social sciences are interested in how a construct changes longitudinally within a given population and are able to choose from a number of sophisticated data modeling techniques that are designed to investigate growth in a construct over time. Perhaps most conventionally, a quantitative outcome is measured directly at multiple time points, and a basic linear growth curve model is applied to estimate global intercept and slope parameters for the population, providing the basis for understanding continuous linear change in the level of an outcome of interest. This straightforward linear growth curve model has a lengthy history of being used to model individual change in educational contexts; for example, estimating reading trajectories among boys with Fragile X syndrome (Adlof et al., 2015) and modeling growth in preschool mathematics learning as a function of teacher-child play interactions (Trawick-Smith et al., 2016).

A general assumption underlying the linear growth model is that the outcome measure follows a continuous probability distribution, and that the model residuals are normally distributed (Fox, 1997). Very commonly, however, the outcome of interest is not measured by a continuously distributed indicator at each time point, but instead the data are categorical in nature. Fortunately, the linear growth model can be easily modified to estimate change in ordered categorical or binary outcomes across time. This family of linear growth models that have been modified to accommodate longitudinal categorical outcomes is appropriately named *generalized* linear growth models (for

example, logistic regression, generalized estimating equations, autoregressive models, etc.). Generalized linear growth models can also be convenient and sometimes necessary solutions for modeling change in continuous outcomes that exhibit enough skew to potentially violate the assumption of normally distributed residuals behind linear growth models, and therefore require recoding into discrete categories.

The previous examples of linear and generalized linear growth models can be applied to longitudinal outcomes that are directly observed by a specific indicator, or perhaps a calculated composite of multiple observed indicators. However, methodological techniques in fields such as structural equation modeling (SEM) tend to be interested in the *structure* of the relationships among a set of measured indicators, thus estimating measures that are technically *unobserved* in the data. In recent years, statistical techniques for handling growth in outcomes that are not directly observed have gained considerable traction. In such instances, the outcome of interest may be considered a *latent* variable, typically identified by a common set of items at each measurement occasion (e.g., latent variable outcomes and latent class variables). For example, depression is often considered a latent variable (i.e., depression factor) that is measured by a set of items related to depression symptomology. Researchers interested in the impact of counseling and/or pharmaceutical interventions on depression symptomology may rely on latent growth models (LGM) to estimate change over time in an overall depression construct, rather than change in each individually measured symptom of depression.

It is clear from the variety of published methodological literature and available software programs that researchers interested in modeling growth have plenty of choices when it comes to selecting the appropriate analysis technique that fits both the nature of their substantive theory and the distributional properties of the data available to them. However, the perfect analysis model may be rendered useless if the underlying measurement characteristics of the observed indicators are not consistent across measurement occasions. Steps should be taken to ensure that the *meaning* of the instrument(s) does not change over time (i.e., the concept of longitudinal measurement invariance holds).

Deciding on a method to analyze longitudinal data should be preceded by a discussion of how the data are distributed, how the measurement properties hold up over time, and conceptualizing the desired growth parameters to describe change. This dissertation intends to focus on one of the many sophisticated techniques used to estimate change in latent constructs over time—the latent transition analysis (LTA) model—and explore how the concept of measurement invariance fits into this modeling framework. This chapter begins with an introduction to the LTA model literature, specifically regarding the measurement and structural aspects of the design. This will be followed by a review of longitudinal measurement invariance concepts and how invariance is often assessed by applied researchers. Finally, a discussion regarding the different ways non-invariance can manifest in an LTA framework will be presented.

LATENT TRANSITION ANALYSIS

Latent transition analysis (LTA) is a form of autoregressive growth model used in the social, behavioral, and health sciences to investigate the probability of transitioning between unobserved subgroups across two or more time points. LTA can be considered a longitudinal extension of the conventional latent class analysis (LCA) procedure, a latent variable mixture model which classifies individuals into mutually exclusive and exhaustive classes based on their response patterns on a set of observed dichotomous indicators. The LCA serves as the measurement model at each time point in an LTA model, and movement between the identified categorical latent classes across time (i.e., the structural model) is typified as an autoregressive process. This autoregressive process follows a Markov structure, modeling status at time t as conditional on status at time $t - 1$. In fact, the LTA model is considered analogous to the latent Markov model (Baum et al., 1970; Vermunt et al., 1999; Wiggins, 1973). An LTA based on two time points would naturally fit a first-order Markov chain model, where status at time t is not regressed on any other time point prior to $t - 1$. If more time points are considered for analysis, a second- or higher-order Markov chain model could be employed, but first-order models are the most common in the applied literature.

Some recent empirical examples of LTA applications illustrate the modeling technique's flexibility across a diverse array of fields. For example, Lee, Chassin, and Villalta (2013) explored transitions in alcohol use profiles in a high-risk sample from adolescence through adulthood to address whether and when a "maturing out" of alcohol involvement occurs. Mathur, Stigler, Erickson, Perry, and Forster (2014) also provide an

application of the LTA model within a substance use framework, wherein the authors examined the potential protective effect of a household smoking ban on transitions in smoking behavior profiles from late adolescence to young adulthood. In two separate studies conducted by Nylund-Gibson (2008) and Williford, Boulton, and Jenson (2014), transitions in peer victimization experiences across the middle school years were investigated using LTA techniques. In the realm of educational research, Ding, Richardson, and Schnell (2013) investigated developmental trajectories of word literacy from kindergarten through the second grade, and Ji, Beerwinkle, Wijekumar, Lei, Malatesha Joshi, and Zhang (2018) used LTA to identify effects of a web-based intelligent tutoring system on Grade 8 reading comprehension.

LTA Measurement Model

As illustrated within the example publications provided above, LTA is an appropriate choice for modeling transitions of unobserved subgroups that are typically identified by separate LCAs at each time point. The LCAs essentially serve as wave-specific measurement models. The current section will provide a formal introduction to the LCA model, presenting notation that will be used throughout this dissertation.

The LCA is directly analogous to the conventional factor analysis model, which aims to produce a factor structure that accounts for the linear relationships among a set of observed variables (Kline, 2016). The latent factor resulting from a factor analysis, which is assumed to be continuous and approximately normally distributed, is expected to hold for all individuals in a population. In comparison, the LCA seeks to model the

interindividual variability in patterns of item responses, with a goal of classifying individuals into homogenous subgroups within the population, thus producing a categorical latent variable with an assumed multinomial distribution (G. H. Lubke & Muthén, 2005). For example, Lee, Chassin, and Villalta (2013) modeled participants' patterns of drinking frequency, drinking quantity, frequency of binge drinking behavior, and symptoms of alcohol use disorder to estimate the following four mutually exclusive and exhaustive alcohol use profiles: Abstainers, Low-Risk Drinkers, Moderate-Risk Drinkers, and High-Risk Drinkers.

The literature distinguishes between these related frameworks as being either *variable-centered* (e.g., factor analysis, conventional regression) or *person-centered* (e.g., LCA, finite mixture modeling) analyses (B. Muthén & Muthén, 2000). To clarify, variable-centered analyses share a goal of uncovering relationships among variables and assume that the identified relationships hold true for all members in a population. On the other hand, person-centered analyses seek to group like individuals into homogenous subgroups, where the structure of the relationship among variables is thought to hold for all members of a specific subgroup but is explicitly different from structures found in other subgroups. Morin, Meyer, Creusier, and Biétry (2016) refer to the resulting latent classes as *prototypical* in nature, with each subject having a probability of membership in an unobserved profile group based on their similarity with the profile's specific response configuration. Person-centered modeling techniques are also referred to as *mixture models*, which include the family of growth mixture models [GMM; e.g., latent class growth analysis (LCGA) and LTA].

The traditional LCA provides a modeling framework in which the set of manifest variables or indicators are measured categorically, although the term “latent class analysis” has been loosely associated with models based on continuous indicators as well. *Latent profile analysis* (LPA; Flaherty & Kiff, 2012; Hadzi-Pavlovic, 2010; Lanza, Flaherty, & Collins, 2003) is the appropriate term for a model in which the categorical latent variable is indicated by a set of continuous manifest variables. Semantics notwithstanding, several available software packages (e.g., *Mplus*, LISREL, SAS, Latent Gold, Stata) offer advanced estimation techniques that can accommodate LCA models based on any combination of variable types (i.e., continuous, binary, ordinal, nominal, and count). For the purpose of simplicity, the proposed dissertation will be limited to discussing LCA and LTA models based on sets of directly observed categorical (specifically, dichotomous) indicators.

Table 2.1 provides a taxonomical breakdown of four variations on the latent variable model, each of which is dependent upon the type (i.e., continuous or categorical) of indicators and the underlying latent variable. All of the latent variable models included in Table 2.1 are well-documented in the methodological literature and have a rich history in applied cross-sectional research.

Table 2.1. Four Different Latent Variable Models

	Continuous latent variable	Categorical latent variable
Indicators treated as continuous	Factor analysis	Latent profile analysis
Indicators treated as categorical	Latent trait analysis or item response theory	Latent class analysis

LCA Model Parameters

The main objective when implementing an LCA model is to obtain a set of latent classes that efficiently distinguishes among patterns of responses in the data. The ensuing objective is to determine how individuals are distributed, or classified, among the set of classes. As such, the LCA provides estimates for two types of model parameters: *item probability* parameters and *class probability* (or *prevalence*) parameters. For each estimated latent class, a set of item probability parameters reveals the probabilities of endorsing each item, conditional on membership in that specific class. The relative prevalence of each latent class within the population is estimated by each class probability parameter.

As an example, Table 2.2 below provides the results from an LCA of adolescent delinquent behavior using public-use data from the National Longitudinal Study of Adolescent Health (Add Health) study (Harris et al., 2009; Lanza et al., 2003), presenting estimates for both class prevalence parameters and class-specific item response probability parameters. The six survey items of interest asked participants whether they

had participated in the following behaviors in the prior year: 1) lying to parents, 2) being publicly loud/rowdy/unruly, 3) damaging property, 4) stealing something from a store, 5) stealing something worth less than \$50, and 6) taking part in a group fight. Unique patterns of item endorsement are presented for each of five estimated latent delinquency classes from the best-fitting model.

Table 2.2. Five-Class Model of Past-Year Delinquency (Add Health Public-Use Data, Wave I; $N = 2,087$)

	Latent Class				
	Non-delinquents	Liars	Verbal Antagonists	Shoplifters	General Delinquents
<i>Latent class prevalences*</i>					
	.24	.27	.25	.13	.10
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.92
Damaged property	.00	.05	.25	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.07	.34	.17	.54

*Latent class prevalences may not sum to 1.00 due to rounding.

From the above example, one of the emerging latent classes, comprising 24% of study participants, can be interpreted as a class of “non-delinquent” adolescents with very low probabilities for endorsing any of the specified behaviors over the past year—note the estimated item response probabilities ranging from 0.00 to 0.15. Parameter estimates for a smaller class (10% of participants) characterize a homogenous group of “generally

delinquent” participants who are highly likely to endorse behaviors related to lying, public disruption, and theft (item response probabilities ranging from 0.85 to 0.92). Three other latent subgroups are formed based on homogenous patterns of item endorsements and are substantively labeled Liars, Verbal Antagonists, and Shoplifters. Following is a formal discussion of the derivation of the two sets of LCA parameters (i.e., class prevalence parameters and item response probabilities), which will occasionally refer to values from Table 2.2 as substantive examples.

As a starting point for conducting an LCA, consider a contingency table of possible item response strings created from $j = 1, \dots, J$ observed items each with $r_j = 1, \dots, R_j$ response categories, thus consisting of $W = \prod_{j=1}^J R_j$ cells, where each cell identifies a unique string of possible item responses. For example, the total number of possible complete response strings from the set of six dichotomous items presented in Table 2.2 would equal $W = 2^6 = 64$. Each of the W response patterns for the set of J items can be represented by the vector $\mathbf{y} = (r_1, \dots, r_J)$, and thus the entire array of possible response patterns, \mathbf{Y} , consists of W rows and J columns. The probability of endorsing a particular response pattern \mathbf{y} is given by $P(\mathbf{Y} = \mathbf{y})$, and it naturally follows that $\sum P(\mathbf{Y} = \mathbf{y}) = 1$.

Considering the adolescent delinquency classes from Table 2.2, a commonly endorsed response string among shoplifters could be given by the vector $\mathbf{y} = (1, 0, 0, 1, 1, 0)$, which is the endorsement of both theft-related behaviors and lying to parents. However, this is not the only response string present in the shoplifting class, as

evidenced by the non-zero probabilities for endorsing the other three delinquent behaviors. Almost half (48%) of adolescents categorized in the shoplifting class admitted to being publicly disruptive in the past year, while property damage and fighting were less frequently endorsed (17% for both). The substantive labeling of the latent class as “Shoplifters” is clearly derived from interpreting the pattern of the more frequently endorsed response string in the group.

Now that the item response strings have been defined in probabilistic terms, consider the underlying latent class variable indicated by the set of J items. Given a latent categorical variable L with $c = 1, \dots, C$ latent classes, the prevalence parameter for class c is represented by $\gamma_c = P(L = c)$. In other words, γ_c is the probability of membership in class c of latent categorical variable L . From the example in Table 2.2, L is the latent delinquency variable indicated by the six delinquent behavior items ($j = 1, \dots, 6$). Based on the underlying data, latent variable L is best modeled by five homogenous classes ($c = 1, \dots, 5$). For example, $\gamma_2 = 0.27$ tells us that 27% of participants (within rounding error) are estimated to be classified in the second latent class, *Liars*. Because the latent classes are assumed to be mutually exclusive and exhaustive, the sum of the latent class prevalence parameters equals 1, as suggested by the following:¹

$$\sum_{c=1}^C \gamma_c = 1.$$

¹ Note that due to rounding, the sum of class prevalence parameters may not sum to 1 when presented in the literature.

Considering the special case wherein the latent class variable is indicated by a set of observed dichotomous, or binary, items where $r_j = \{0,1\}$ for all $j \in J$ (e.g., as in the adolescent delinquency model presented in Table 2.2), the *marginal probability* of endorsing item j [i.e., $P(r_j = 1)$] is given by

$$P(r_j = 1) = \sum_{c=1}^C P(L = c)P(r_j = 1|L = c),$$

where the *conditional probability* of endorsing item j , given membership in latent class c , is defined by the following logistic regression equation:

$$P(r_j = 1|L = c) = \frac{1}{1 + \exp(-v_{jc})}.$$

Here, v_{jc} represents the logit associated with each of the j s within each latent class, c .

Therefore, the joint probability of an entire response string, assuming *conditional independence*, is given by

$$\begin{aligned} P(Y = \mathbf{y}) &= P(r_1, r_2, \dots, r_J) = \sum_{c=1}^C P(L = c)P(r_1, r_2, \dots, r_J|L = c) \\ &= \sum_{c=1}^C P(L = c)P(r_1|L = c)P(r_2|L = c) \dots P(r_J|L = c) \\ &= \sum_{c=1}^C \gamma_c \prod_{j=1}^J P(r_j|L = c). \end{aligned}$$

The assumption of conditional independence (also referred to as *local independence*) for the LCA model specifies that observed indicators are independent of each other *within* latent classes. This means that there is no within-class error covariance among the j s, as

the correlation among the j s is thought to be fully explained by the latent class variable. Figure 2.1 illustrates the conventional LCA model. Note that a violation of conditional independence would occur if the errors associated with any of the indicators were allowed to covary.

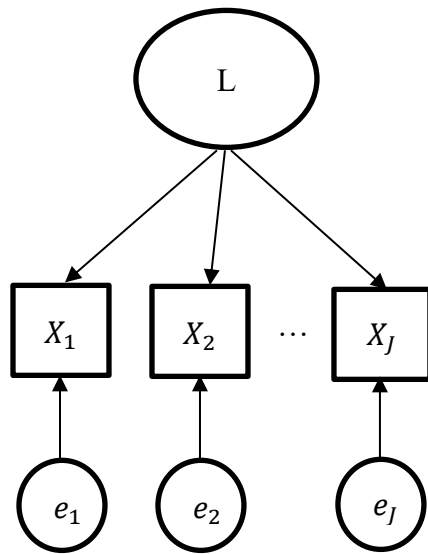


Figure 2.1. The Latent Class Analysis Model: Latent variable L indicated by J observed variables (i.e., X_1, X_2, \dots, X_J) and non-covariance among error terms (i.e., conditional, or local, independence)

Interpretation of Latent Classes

As was illustrated by the adolescent delinquency example, the conditional item response probabilities are particularly useful with regards to assigning substantive meaning to each of the latent classes. In order to facilitate interpretation, many applied researchers choose to visualize these probabilities with item probability plots, as shown

by an example in Figure 2.2. Each observed item is displayed along the *x-axis*, and conditional item probabilities for each latent class are plotted against values along the *y-axis*. The adolescent delinquency model shown in Figure 2.2 provides an example of an *unordered solution*, in which some of the latent class profiles intersect, reflecting a mixture of high and low probabilities of item endorsement within each latent class (item response probabilities are sourced from Table 2.2).

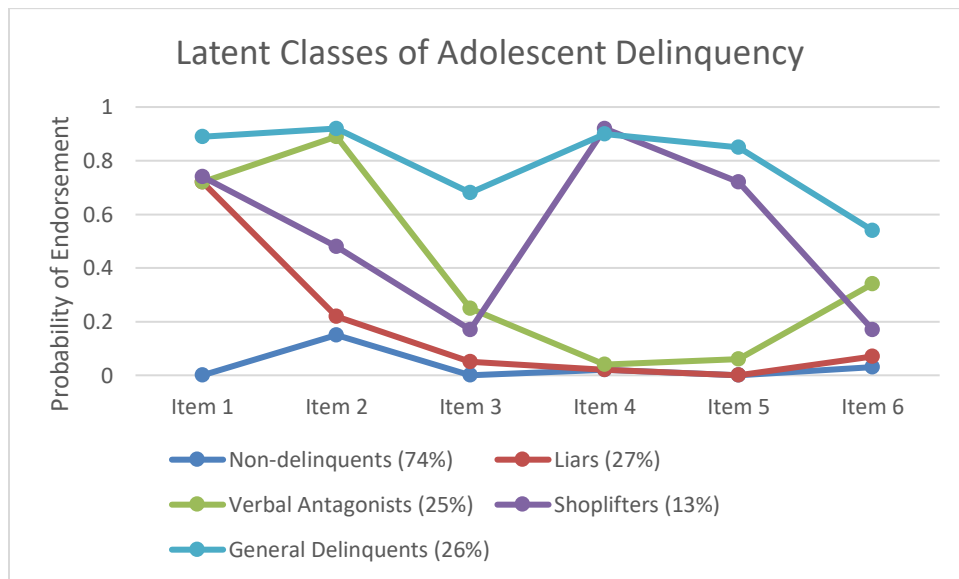


Figure 2.2. Item probability plot for latent classes of adolescent delinquency

An *ordered solution* is illustrated in the hypothetical item probability plot shown in Figure 2.3. In this case, the best-fitting LCA produced two latent classes: non-

delinquents and general delinquents.² Individuals assigned to the general delinquents class are highly likely to endorse four of the six delinquent behaviors and moderately likely to endorse the other two, while those in the non-delinquent class have a very low probability of endorsing any of the delinquent behaviors. Ordered LCA solutions are also evident in knowledge acquisition research because the *stage-sequential* nature of learning yields an LCA framework where individuals in class c are assumed to have gained more knowledge than those belonging to classes $1, \dots, (c - 1)$.

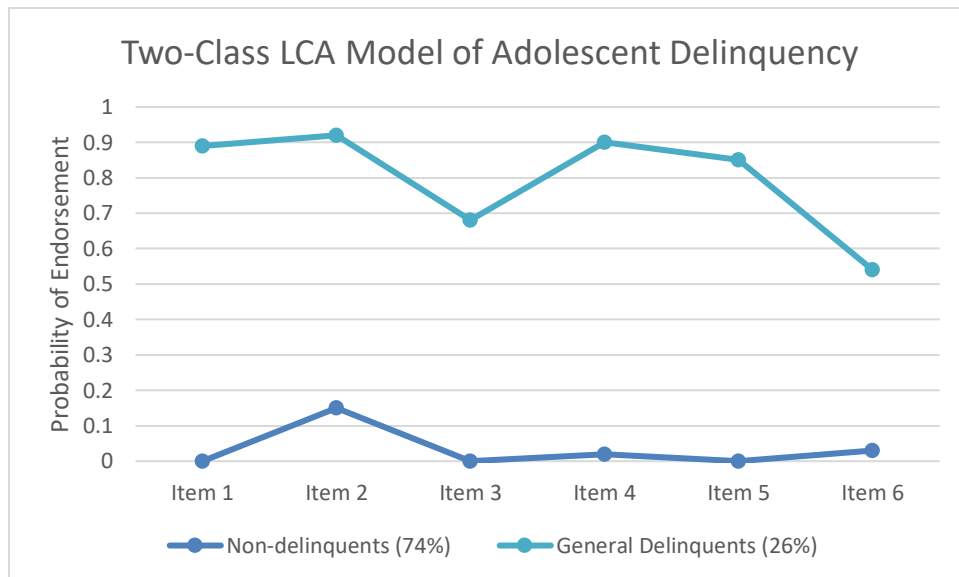


Figure 2.3. Item probability plot for a hypothetical two-class LCA model of adolescent delinquency

² Several steps should be considered when determining the “best fitting” latent class model. A more detailed approach to assessing model fit within the LCA and LTA frameworks is provided later in the chapter.

Taking into consideration the visual patterns of item response probabilities (along with each observed item's content and phrasing), a researcher is able to judge 1) whether their model's solution is in concordance with substantive theory, and 2) how to meaningfully interpret the characteristics of each emerging latent class.

Homogeneity and latent class separation

Another useful technique to assist in latent class interpretation is the evaluation of the overall patterns of item response probabilities via the concepts of *homogeneity* and *latent class separation*. Parallels for both criteria can be found in factor analysis (FA). Specifically, homogeneity in LCA is analogous to factor saturation in FA, which describes the degree to which the absolute values of the item loadings are high on a particular factor.³ The concept of latent class separation in LCA is analogous to that of simple structure in FA—when individual factors are clearly identified by a pattern of loadings. Both homogeneity and latent class separation are desirable attributes of a latent class solution and provide valuable information about latent class characteristics beyond the numerical value of each item's response probability. It is highly unlikely that perfect homogeneity or latent class separation will be present in an applied setting; however, they are appropriate concepts against which one should gauge an LCA solution. Following is a more detailed explanation of homogeneity and latent class separation.

³ Recall that factor loadings in factor analysis are regression coefficients representing the correlation between the indicator and the latent factor and range from -1 to 1.

Homogeneity in the LCA framework refers to the degree to which members of latent class c are likely to provide the same pattern of observed responses. In other words, a latent class c is highly homogenous when one response pattern is particularly characteristic of that class [e.g., recall the common response pattern exhibited by the Shoplifter class: $\mathbf{y} = (1,0,0,1,1,0)$]. The concept of perfect homogeneity is defined when *all* participants belonging to a latent class endorse identical response patterns; that is, $P(r_j|c) = 0$ or 1 for all variables j . Therefore, only one response pattern \mathbf{y}' will exist for which $P(\mathbf{Y} = \mathbf{y}'|L = c) = 1$, and all remaining response pattern options will have a probability of 0 . It follows that latent classes with high homogeneity will display conditional item probabilities very close to 1 or 0 . Conversely, low latent class homogeneity aligns with conditional item response probabilities that are further away from 1 or 0 (i.e., closer to $.5$), suggesting that more than one pattern of responses is characteristic of members within that latent class.

In factor analysis, the ideal concept of simple structure is attained when each observed variable loads highly on only one factor, thus facilitating a distinct conceptual contrast among the set of factors. Similarly, latent class separation is at a maximum when there is a clear differentiation among the class-specific response patterns. In other words, high latent class separation is evident when a response pattern that is particularly characteristic of one latent class is not likely to be endorsed by any of the other latent classes. Perfect latent class separation is defined when $P(\mathbf{Y} = \mathbf{y}'|L = c') = 1$ and $P(\mathbf{Y} = \mathbf{y}'|L = c) = 0$ for all $c \neq c'$. As is the case with perfect homogeneity, perfect latent class separation is unlikely to be observed in empirical research, but high levels of

class separation are still desired. It follows that high latent class separation occurs when $P(Y = \mathbf{y}'|L = c')$ is much greater than $P(Y = \mathbf{y}'|L = c)$ for all $c \neq c'$. The hypothetical two-class solution presented earlier in Figure 2.3 illustrates strong latent class separation.

Posterior class probabilities

Again, the LCA produces two types of parameters: class prevalence parameters [presented earlier as $\gamma_c = P(L = c)$] and conditional item response probabilities for each class [i.e., $P(r_j|c)$]. In addition to the two main types of parameters, applied researchers may be interested in calculating an *individual's* probability of membership in each latent class, conditional on their observed string of item responses (i.e., *posterior class probabilities*). This is analogous to the calculation of individual factor scores in a factor analysis, and is given by

$$P(L = c|r_1, r_2, \dots, r_J) = \frac{P(L = c)P(r_1|L = c)P(r_2|L = c) \dots P(r_J|L = c)}{P(r_1, r_2, \dots, r_J)}.$$

Therefore, if an LCA produces a best-fitting three-class solution, three separate posterior class probabilities can be calculated for each individual who provided a complete response string. In a procedure known as *modal class assignment*, an individual is assigned to the latent class for which they have the highest probability of membership. This is a useful technique to produce an “observed” categorical variable to explore the relationships between class assignment and external variables via standard methods (e.g., logistic regression) (Bakk et al., 2016).

LTA Structural Model

As mentioned above, the LTA is considered a longitudinal reparameterization of the LCA, where separate LCAs serve as wave-specific measurement models and are connected longitudinally via an autoregressive relationship (Bray et al., 2010; Karen Lynn Nylund, 2008). Figure 2.4 below illustrates an LTA model with repeated measures on the set of J latent class indicators observed at each of three time points.⁴

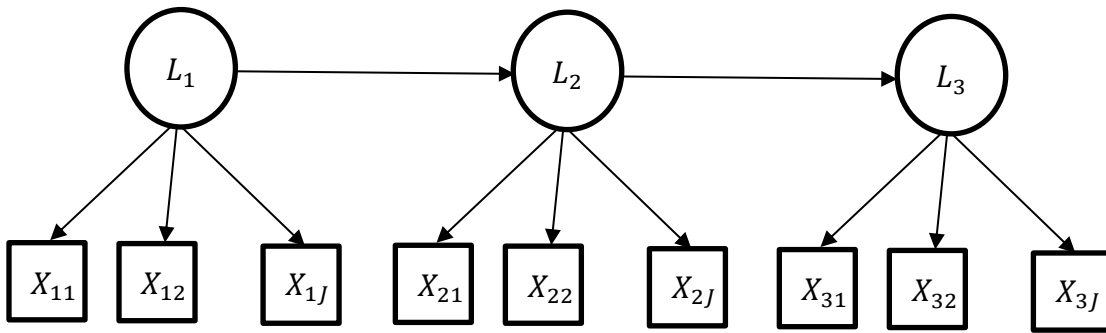


Figure 2.4. A latent transition analysis model with J latent class indicators measured at three time points

The dynamic nature of the LTA allows individuals to transition among latent classes between time points—reflecting this temporal aspect, some researchers may refer to the latent classes in LTA as *latent statuses*. In Figure 2.4 above and in subsequent discussions of observed items within a longitudinal setting, note the additional subscript referencing the specific time point, t , where $t = 1, 2, \dots, T$. As it is an extension of the

⁴ Note that the latent class status at time point t is regressed only on the status at time $t - 1$, indicating that this model follows a first-order Markov chain autoregressive process.

LCA, the LTA estimates latent class probabilities (i.e., γ_c) at each time point as well as class-specific item response probabilities for each set of manifest indicators at each measurement occasion. An additional set of parameters estimated by an LTA are referred to as *transition probabilities*, which are defined by the probability of latent class membership at time t conditional on latent class membership at time $t - 1$, and are often represented by τ . Before providing the fundamental equation for transition probabilities estimated by LTA, it is critical to first introduce the formulation of the first-order autoregressive process relating repeated measures of a directly observed categorical variable.

Autoregressive model with observed categorical variables

Conventional growth curve models (GCM), which describe longitudinal change via continuous growth factors (e.g., intercept, linear slope), are a natural fit when investigating continuously distributed variables that are measured at repeated time points. Alternatively, growth can be assessed within an autoregressive (AR) modeling framework, where an individual's outcome at time t behaves as a function of the same outcome measured previously, and thus change is described via time-adjacent relationships. An AR process that models outcomes based on p previous observations is commonly referred to as an AR model of order (or degree) p . For example, a *first-order* AR model regresses outcomes at time t on outcomes only at time $t - 1$ (e.g., y_2 on y_1 and y_3 on y_2 , etc.), whereas a *second-order* AR model entails regressing outcomes at

time t on those at time $t - 2$ (e.g., y_3 regressed on y_1 , and y_4 on y_2 , etc.). Figure 2.5 provides an illustration of a first-order AR model with four measurement occasions.

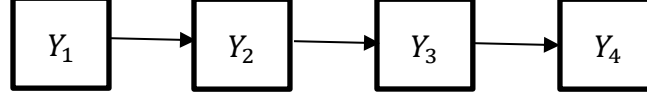


Figure 2.5. Path diagram for a generic first-order autoregressive model

The time-adjacent relationships estimated by the AR model are expressed with conditional probabilities, providing a logical framework for analyzing change in categorical outcomes. In a first-order AR model, the association between a categorical variable at time t with itself at time $t - 1$ is thus specified as a multinomial logistic regression. As a refresher to multinomial logistic regression, first consider the case whereby an observed categorical outcome variable C (with $k = 1, \dots, K$ response options) is regressed on a *continuous* covariate, X . The conditional probability of $C = k$ given $X = x$ can be expressed as follows:

$$P(C = k|X = x) = \frac{\exp(\alpha_k + \beta_k x)}{\sum_{k=1}^K \exp(\alpha_k + \beta_k x)},$$

where $\alpha_K = 0$ and $\beta_K = 0$ when the last response category, K , serves as the reference category.

Applying this parameterization to a longitudinal setting, for a first-order AR application with categorical outcomes, the above equation can be altered to reflect the regression of categorical variable C_t on itself at the previous time point, C_{t-1} . Because

the multinomial logistic regression treats all covariates as continuous, categorical covariates of interest must be first transformed into a set of “dummy coded” variables to be included in the analysis (Reboussin et al., 1998). A categorical predictor with M categories will be represented by $M - 1$ dummy variables, with the M^{th} category acting as the reference. The following equation illustrates an AR model with a three-level categorical outcome measured at two time points:

$$P(C_t = k | C_{t-1} = m) = \frac{\exp(\alpha_k + \beta_{1k}d_1 + \beta_{2k}d_2)}{\sum_{i=1}^3 \exp(\alpha_i + \beta_{1i}d_1 + \beta_{2i}d_2)}$$

where $d_1 = 1$ when $C_{t-1} = 1$ and $d_2 = 1$ when $C_{t-1} = 2$, assuming the third category at time $t - 1$ serves as the reference. Further, α_3 , β_{13} , and β_{23} are all equal to zero, assuming the third category at time t serves as the reference. Therefore, the multinomial logistic regression offered by the equation above would yield six parameters: $\alpha_1, \alpha_2, \beta_{11}, \beta_{12}, \beta_{21}$, and β_{22} , where each β represents the difference in the log odds (i.e., logits) between individuals in the designated dummy category and those in the reference category (i.e., $C_t = k$ versus $C_t = K$, the latter resolving to $C_t = 3$ for the above example equation which illustrates a three-level categorical outcome).

The conditional probabilities estimated by an AR model with categorical variables are also referred to as *transition* probabilities, and it is often practical to present the set of these probabilities as a transition matrix. Again, these values represent the probability of transitioning to a particular category at time t , given previous category status at time $t -$

1. Table 2.3 illustrates a transition matrix for a three-level categorical variable measured at two time points. Note that the probabilities along the diagonal reflect *stability*, or lack of transitioning between categories.

Table 2.3. Transition matrix for a three-level categorical variable measured at two time points

	C_t		
C_{t-1}	1	2	3
1	$P(C_t = 1 C_{t-1} = 1)$	$P(C_t = 2 C_{t-1} = 1)$	$P(C_t = 3 C_{t-1} = 1)$
2	$P(C_t = 1 C_{t-1} = 2)$	$P(C_t = 2 C_{t-1} = 2)$	$P(C_t = 3 C_{t-1} = 2)$
3	$P(C_t = 1 C_{t-1} = 3)$	$P(C_t = 2 C_{t-1} = 3)$	$P(C_t = 3 C_{t-1} = 3)$

The LTA model

As previously mentioned, the LTA consists of wave-specific LCA measurement models that are related by an autoregressive process between adjacent waves. Similar to the general AR process described above, there are $T - 1$ points of transition in an LTA model with $t = 2, \dots, T$ repeated measurement occasions, and the calculation of LTA transition probabilities is analogous to the multinomial logistic regression equation for an AR model with categorical outcomes. Instead of modeling change between *observed* categorical outcomes (e.g., autoregressive model), the focus is now on transitioning among *latent* categories (i.e., latent classes). Consider a three-class LCA solution modeled at two time points, where k represents class specification at time t (i.e., $k =$

1,2,3) and m represents class specification at time $t - 1$ (i.e., $m = 1,2,3$). The probability of transitioning to latent class k given previous latent class membership m is expressed by the following:

$$\tau_{km} = P(C_t = k | C_{t-1} = m) = \frac{\exp(\alpha_k + \beta_{1k}d_1 + \beta_{2k}d_2)}{\sum_{i=1}^3 \exp(\alpha_i + \beta_{1i}d_1 + \beta_{2i}d_2)}.$$

The literal interpretation of each β coefficient within the above equation is fairly straightforward and is typically presented as an odds ratio given by $\exp(\beta_{mk})$. This refers to the ratio of the odds of membership in Class k at time t versus Class K (or Class 3, the reference class in this example) for individuals belonging to Class m at time $t - 1$, compared to those belonging to Class M at the previous measurement occasion (also Class 3, the reference category at time $t - 1$).

Note that the number of transition matrices estimated by an LTA model is equal to the number of points of transition (unless they are constrained to equality across transition points). For example, an LTA model with $T = 2$ measurement occasions will have $T - 1 = 1$ point of transition, and therefore only one matrix of transition probabilities will be estimated. The matrix of transition probabilities associated with the three-class example above is presented as follows:

$$\begin{bmatrix} \tau_{11} & \tau_{21} & \tau_{31} \\ \tau_{12} & \tau_{22} & \tau_{32} \\ \tau_{13} & \tau_{23} & \tau_{33} \end{bmatrix}.$$

At each time point, t , latent class membership is mutually exclusive and exhaustive; therefore, each row of the transition probability matrix sums to 1, which is expressed by the following:

$$\sum_{c_t}^C \tau_{c_t|c_{t-1}} = 1.$$

Transition probabilities, τ , are critical elements within what is known as the fundamental expression for LTA, which essentially formulates the probability of an individual's entire response string for a set of J indicators across T measurement occasions. First, consider the elements of these response strings across time points $t = 1, \dots, T$ for $j = 1, \dots, J$ dichotomous items. A response string, \mathbf{y} , is given by the following:

$$\mathbf{y} = (r_{1_1}, \dots, r_{J_1}, \dots, r_{1_T}, \dots, r_{J_T}).$$

The probability of observing a particular vector of responses, \mathbf{y} , is therefore a function of the probability of latent class membership for each latent class at the first measurement occasion (i.e., when $t = 1$; γ_{c_1} for all $c = 1, \dots, C$ latent classes), the probabilities of transitioning to a particular latent class at time point t conditional on latent class membership at time $t - 1$ (i.e., the τ s), and the class-conditional item response probabilities at each time point (i.e., $\rho_{r_{j,t}|c_t}$). The equation below provides the mathematical basis for the estimation of the LTA model:

$$P(Y = \mathbf{y}) = \sum_{c_1=1}^C \dots \sum_{c_T=1}^C \gamma_{c_1} \tau_{c_2|c_1} \dots \tau_{c_T|c_{T-1}} \prod_{t=1}^T \prod_{j=1}^J \rho_{r_{j,t}|c_t}$$

In a model with two time points, this equation reduces to the following:

$$P(Y = \mathbf{y}) = \sum_{c_1=1}^C \sum_{c_2=1}^C \gamma_{c_1} \tau_{c_2|c_1} \prod_{t=1}^2 \prod_{j=1}^J \rho_{r_{j,t}|c_t}$$

The calculation for the latent class prevalence for time t , where $t = 2, \dots, T$, is a function of the class prevalence at time $t - 1$ and the transition probabilities:

$$\gamma_{c_t} = \sum_{c_{t-1}=1}^C \gamma_{c_{t-1}} \tau_{c_t|c_{t-1}}$$

LTA Model Specifications

This section will discuss some general procedural steps suggested for implementing the basic LTA model in an applied setting, as well as the incorporation of important model specifications at both the measurement and structural level that may allow for increased parsimony and address specific hypotheses.

Fitting the measurement model at each time point

As stated previously, the LCA is the most commonly adopted measurement model for LTA in applied research (Bray et al., 2010; Lanza et al., 2003). In determining the best-fitting measurement model at each time point, a researcher is faced with a series of important decisions regarding *class enumeration*, which entails the assessment of the relative fit of competing models of increasing numbers of classes. Many of the useful tools available to aid the researcher in these decisions will be summarized below. It should always be noted, however, that the selection of the ultimate measurement model is to be rooted in a combination of statistical criteria, model parsimony, and substantive interpretation.

Assessment of the relative fit of competing latent class models entails fitting a series of LCA models, typically starting with a two-class solution and increasing the number of classes by one until either substantive interpretation is threatened or convergence issues arise. While there is not an agreed upon *single* criterion for estimating the correct number of latent classes in a population, recent research has been devoted to evaluating the accuracy and power of several currently used criteria. Most commonly, a combination of likelihood ratio difference tests (LRT) and information criteria (IC) is used, in addition to the more subjective criteria of meaningful interpretability (Nylund, Asparouhov, & Muthén, 2007).

Although latent class models that differ by one class (e.g., a $k - 1$ class solution versus a k class solution) are technically nested models, the traditional difference test of the likelihood ratios provided by both models cannot be applied due to the necessary

statistical properties not being met. In general, because the $k - 1$ class solution is a special case of the k class solution where the probabilities associated with one class are fixed at zero, the resulting difference in log likelihood values does not follow a chi-square distribution (Nylund et al., 2007). Alternative likelihood ratio difference tests are available for the comparison of sequential latent class models, including the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo, Mendell, & Rubin, 2001) and the bootstrap likelihood ratio test (BLRT; described in McLachlan & Peel, 2005). The LMR-LRT was developed to be an approximation to the traditional LRT and produces a p -value for comparing the fit between neighboring class models. A significant p -value (e.g., $p < .05$) points to a significant improvement in fit when an additional class is added to the model. A non-significant p -value would suggest no significant improvement in fit accompanying the addition of an extra class, and in such a case, the more parsimonious model would typically be preferred. The parametric bootstrap LRT (BLRT) empirically estimates the distribution of difference scores using bootstrapped samples instead of assuming a chi-square distribution. Similar to the LMR-LRT, the BLRT also provides a p -value to assess relative fit. The interpretation of the BLRT p -value is identical to that of the p -value produced by the LMR-LRT. Both of these alternative LRT procedures can be summoned in a variety of statistical packages (e.g., output commands TECH11 and TECH14 in *Mplus*, B. O. Muthén & Muthén, 2012; LCA Bootstrap Macro for SAS, Dziak, Lanza, & Xu, n.d.); however, they tend to be available for LCA, not LTA, model frameworks.

Also considered in the assessment of relative, or comparative model fit are statistical information criteria (IC), such as Akaike's Information Criterion (AIC;

(Akaike, 1987) and the Bayesian Information Criterion (BIC; Schwarz, 1978). These are sometimes referred to as penalized fit statistics because they each impose a penalty on each model's log-likelihood statistic. The AIC adds a penalty based on the number of parameters (P) estimated by the latent class model:

$$AIC = -2 \log L + 2P,$$

while the BIC penalty is based on both P and sample size (N):

$$BIC = -2 \log L + [\log(N)]P.$$

There also exists an Adjusted BIC (ABIC; Sclove, 1987) which changes the sample size penalty in the BIC equation above by replacing N with N^* , where $N^* = (N + 2)/24$, and the Consistent AIC (CAIC; Bozdogan, 1987) which replaces $2P$ in the AIC equation above with $P(\log(N) + 1)$. When comparing these penalized fit statistics, smaller values reflect a preferred balance of model fit and parsimony, and it would follow that the model with the minimum IC is the best choice. However, there is often disagreement among the ICs due to the differing types of penalties imposed. For this reason, ICs are more commonly used for narrowing down the set of latent class solutions than in singling out a clear choice (Dziak et al., 2020). Both the BLRT and BIC have been shown to outperform other tests of relative fit in recent class enumeration simulation studies (Jedidi et al., 1997; Karen L. Nylund et al., 2007; Yang, 2006). Further, simulation studies have

shown that the AIC and LMR-LRT are prone to over- and under-extracting the incorrect number of latent classes (e.g., Diallo, Morin, & Lu, 2016; Karen L. Nylund et al., 2007; Peugh & Fan, 2015; Yang, 2006). However, given the highly parameterized nature of the proposed simulated models, it may be preferable to use an IC that assigns a lower penalty for model complexity (e.g., AIC compared to BIC). The AIC, BIC, ABIC, and CAIC, which are all available in or directly calculable from *Mplus* output for LTA models, will each be considered and compared for class enumeration decisions in this study.

It is important to note that the aforementioned tests of model fit are all heavily influenced by sample size (Marsh et al., 2009) such that, given an adequately large sample size, they may suggest a continuous addition of latent classes. For this reason, many researchers prefer to assess the series of fit statistics visually, via an “elbow plot.” In an elbow plot, the point after which the slope “flattens” suggests the model with the ideal number of latent classes.⁵ Finally, class-specific entropy values are estimated to assess the precision by which individuals are assigned to classes, with values varying from 0 to 1 (higher values suggesting higher classification precision). While entropy values are often considered in the *interpretation* of latent class models, they should not be used as a criterion for model fit (G. Lubke & Muthén, 2007). As it is rarely a good idea to arrive at a class enumeration decision based on one criterion alone, the above tests of statistical fit should always be accompanied by a certain degree of subjectivity, in which

⁵ The process of visually inspecting fit statistics in an elbow plot is not unlike examining scree plots in traditional exploratory factor analyses. However, whereas scree plots are inspected for the first significant “bend” in the slope, the elbow plots are inspected for the first plateauing of the slope – that is, the point after which decreases in slope become negligible.

the researcher considers the substantive meaning and theoretical conformity of each estimated latent class solution.

Structural model specifications/restrictions

The prior section provided general guidelines for assessing model fit for each of the time-specific LCA models within the LTA framework, leading the researcher to make a well-grounded class enumeration decision for each measurement model. A similar fit-assessment procedure is deployed when estimating the overall LTA model, and will be described in further detail during the discussion regarding longitudinal measurement invariance.

The LTA is a particularly flexible statistical model, offering the applied researcher ample opportunities for model specification to meet a variety of needs. Ranging in complexity, common modeling extensions found in the applied literature include the addition of covariates, distal outcomes, and higher order effects. The restriction of model parameters is also an extremely useful manipulation of the basic LTA model, and will be discussed further in this section. Restrictions can be applied to any of the LTA model's parameters (i.e., class prevalence parameters, item response probabilities, transition probabilities), and typically function by *fixing* or *constraining* parameters. A parameter that is fixed has been assigned a specific numeric value (e.g., between 0 and 1 for probability parameters) and will not be estimated by the model. That is, fixed parameters are not accounted for in the total number of parameters (P) estimated by the LTA. When a parameter is constrained, it has been restricted to equivalence along

with a set of other parameters (if any). Thus, the entire set of constrained parameters accounts for a single estimated parameter in the model. An LTA model can generally accommodate any combination of fixed, constrained, or freely estimated parameters. It follows that parameter restriction aids in model parsimony and may protect against issues of non-convergence; however, this type of modeling specification is additionally instrumental in the testing of specific research hypotheses. The subsequent discussion focuses on the restriction of the three types of LTA parameters: latent class prevalences, item response probabilities, and transition probabilities.

Restrictions on latent class prevalence parameters

Restrictions on latent class prevalence parameters are parameter restrictions not likely to be found in the applied LTA literature unless a researcher is interested in testing specific hypotheses about the distribution of latent classes within and across measurement occasions. Typically, the substantive focus in LTA is on the *movement* between classes over time, and restrictions to latent class prevalence parameters at any time point will have a direct effect on how participants are estimated to transition in latent class status across measurement occasions (i.e., will impact the estimated transition matrix). In sum, while it is technically possible to fix or restrain these prevalence parameters in the LTA model syntax, it is not a common path of interest in the applied literature.

Restrictions on item response parameters

While not a necessary restriction for LTA, constraining the conditional item response probabilities to equality across measurement occasions enables the

interpretation of latent classes to remain consistent across time, and is a typically imposed parameterization in the applied literature. This restriction technique presumes *longitudinal measurement invariance* and is both conceptually and practically important for the estimation of an LTA model. The interpretation of elements within the transition matrix becomes much more straightforward when the number and type of latent classes is identical within each LTA measurement model. As an example, an element along the diagonal of the transition matrix, τ_{kk} , represents the probability of membership in class k at time t , conditional upon membership in the same class k at the previous time point, $t - 1$. If the set of conditional item response probabilities for latent class k are not statistically identical at both time points, then the conceptual meaning of latent class k has changed in some way, which renders the interpretation of τ_{kk} ambiguous.

Testing the comparative fit of nested LTA models with and without restrictions on conditional item response probabilities using traditional fit indices described above is one step in assessing longitudinal measurement invariance in the LTA framework, and is described more formally in subsequent sections.

Restriction on transition probabilities

A variety of developmental hypotheses can be directly addressed by restricting specific transition probabilities in the LTA model. A researcher may be interested in whether a significant amount of movement between classes is actually present in the data. Or, given an ordered set of latent classes that ranges in severity or dimension, it may be relevant to assume that movement occurs in one direction only (e.g., as in stage-sequential research). LTA models that include restrictions on transition parameters are

statistically nested within LTA models where the transition probabilities are allowed to be freely estimated; therefore, specific hypotheses regarding the nature of change can be assessed with the comparison of likelihood ratios (e.g., BLRT, LMR-LRT). In such a comparison, a significant chi-square value would indicate that the more restricted model fits significantly worse than the less restricted model, and the additional parameters estimated in the model are necessary. On the other hand, a non-significant difference in fit between the two models would provide evidence in support of the more parsimonious model.

To illustrate, consider an application in which a researcher wishes to test whether any movement at all occurred between four latent classes across two time points. In other words, she is looking to test against a null hypothesis of strict stability. Two models will be compared: Model 1, which allows all elements in the transition matrix to be freely estimated, and Model 2, which restricts all “movement” to the diagonal of the transition matrix. The restricted transition matrix for Model 2 would be constructed by the following (i.e., fixing all elements in the diagonal to 1 and all off-diagonal elements to 0):

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Restricting the elements of a transition matrix to reflect uni-directional change is another common specification built on the traditional LTA. For example, the latent classes may be measuring a cumulative skill or trait (e.g., novice, intermediate, and advanced latent ability classes), in which case “backwards” movement is nonsensical. Assuming the latent classes are ordered in an increasing fashion along the dimension, the researcher may want to model a more parsimonious model using the following restricted transition matrix:

$$\begin{bmatrix} * & * & * & * \\ 0 & * & * & * \\ 0 & 0 & * & * \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

In this case, elements in the lower portion of the transition matrix are fixed at 0, thus forcing no “backwards” movement, and those indicated with an asterisk are freely estimated. Individuals in the most advanced latent class at time $t - 1$ are expected to remain stable, which is illustrated by fixing that transition parameter to 1. Whether researchers are aiming for a more parsimonious model or assessing specific developmental hypotheses, there are many LTA applications that can justify the restriction of transition probability parameters. For further reading and a more detailed discussion on parameter restrictions, see Collins, Graham, Rousculp, & Hansen, 1997; Collins, Hyatt, & Graham, 2000; and Lanza et al., 2003.

LONGITUDINAL MEASUREMENT INVARIANCE

When comparing groups with respect to an observed or latent construct, it is critical that the construct is interpreted similarly by the different populations. In other words, it is undesirable for the measurement properties of observed variables to vary by some group-level factor (e.g., gender, ethnicity). *Measurement invariance* is an umbrella term used to refer to various types of equivalencies among measurement properties (e.g., invariance of item intercepts, factor loadings, unique variances, etc.; Borsboom, Mellenbergh, & Van Heerden, 2002; Horn & McArdle, 1992; Millsap, 2007, 2011; Vandenberg & Lance, 2000). As succinctly stated by the oft-cited Horn and McArdle (1992):

The general question of invariance of measurement is one of whether or not, under different conditions of observing and studying phenomena, measurement operations yield measures of the same attribute. If there is no evidence indicating presence or absence of measurement invariance – the usual case – or there is evidence that such invariance does not obtain, then the basis for drawing scientific inference is severely lacking: findings of differences between individuals and groups cannot be unambiguously interpreted. (p. 117)

It follows, then, that the concept of measurement invariance (MI) can be extended beyond cross-sectional, across-group invariance to encompass the equivalence of a construct's measurement properties across measurement occasions (i.e., *longitudinal measurement invariance*; LMI). From a researcher's viewpoint, the concern is whether change in responses on an observed indicator across measurement occasions truly reflects a change in the underlying latent construct, or if that change is muddled by a shift in the

psychometric properties of the indicator. On LMI, McArdle (2007) states that “although the same variables are measured at repeated occasions, this does not ensure that the same constructs are being measured at each occasion.” Potential causes for these shifts in psychometric properties may include an experimental intervention between measurement occasions, and/or a developmental change in the respondents that alters the operational definition of the measured variable. An example of the latter could be seen in potential differences in the concept of perceived discrimination, as measured by a set of variables which are interpreted differently when participants are adolescents compared to later measures taken during their teenage years, perhaps due to emotional maturation or life experiences.

While across-group MI has been extensively researched from a methodological perspective and regularly incorporated into the applied literature (Vandenberg & Lance, 2000), there is far less available information on LMI – either regarding the possible types of non-invariance, or whether departures from LMI seriously impact the interpretation of any resulting model-specific longitudinal parameter estimates. Further, most of the existing research on LMI is presented in the CFA framework (de Beurs et al., 2015; Fokkema et al., 2013; Makhubela & Mashegoane, 2016; Motl et al., 2011). The subsequent sections are intended to provide the reader with a formal definition of MI and LMI, followed by an introduction to how LMI violations may manifest within the LTA universe and methods for statistically testing for the presence of such non-invariance.

Measurement Invariance: Introduction

Measurement invariance, or the absence of bias within a construct, is formally defined by Mellenbergh (1989) as conditional independence in the across-group framework:

$$P(\mathbf{X}|\mathbf{L}, \mathbf{V}) = P(\mathbf{X}|\mathbf{L}),$$

where \mathbf{X} is a vector of observed variables, \mathbf{L} is a vector of the underlying latent variables for \mathbf{X} , and \mathbf{V} contains indicators defining group membership. This equation states that the conditional probability of observing \mathbf{X} given \mathbf{L} is independent of \mathbf{V} . In a single-factor example, measurement invariance holds when individuals matched on \mathbf{L} have the same probability of responses on the set of indicator variables, \mathbf{X} , regardless of differing group membership, \mathbf{V} . If Equation (X) above fails to hold, the distribution of responses to observed variables \mathbf{X} , conditional on matched values of \mathbf{L} , will differ for at least one group defined in \mathbf{V} :

$$P(\mathbf{X}|\mathbf{L}, \mathbf{V}) \neq P(\mathbf{X}|\mathbf{L}).$$

Extending this notion to reflect MI across measurement occasions instead of subgroups (i.e., longitudinally, instead of cross-sectionally), simply replace the grouping variable \mathbf{V} with a timing variable \mathbf{T} :

$$P(\mathbf{X}|\mathbf{L}, \mathbf{T}) = P(\mathbf{X}|\mathbf{L}),$$

indicating the equivalence of response probabilities on a set of observed indicators across time points in \mathbf{T} , given latent class membership in \mathbf{L} , and the lack of LMI indicated by

$$P(\mathbf{X}|\mathbf{L}, \mathbf{T}) \neq P(\mathbf{X}|\mathbf{L}).$$

Measurement Invariance in Multiple-Group LCA Models

It is often desirable to test the equivalence of a latent class structure between two or more observed groups, which is commonly accomplished by the aptly-named *multiple-group LCA*. Consider adding a grouping variable, V , with $q = 1, \dots, Q$ groups, to the conditional probability notation for a single-group LCA with $c = 1, \dots, C$ latent classes identified by a set of J dichotomous items. Maximum equality across groups in the LCA framework is fulfilled when the following conditions are met:

- $P(r_j|c, q) = P(r_j|c, q')$, for all items j , latent classes c , and groups q, q' ;
- $C_q = C_{q'}$, for all groups q, q' ; and
- $\gamma_{c|q} = \gamma_{c|q'}$, for all latent classes c , and groups q, q' .

This means that item response probabilities, $P(r_j)$, for each observed dichotomous indicator j are equivalent across groups q within each latent class c . In other words, the interpretation of the latent classes is the same for all groups. Further, the number of distinct latent classes estimated, C , is equal across groups, as are the class prevalence parameters, γ_c . A less restrictive – but potentially substantively interesting – group comparison entails groups that are identical on the number of latent classes and item

response probabilities, but differ on class prevalence parameters (i.e., $\gamma_{c|q} \neq \gamma_{c|q'}$). In this situation, a researcher may be interested in how subgroups are differentially distributed across classes.

Since both of the previous scenarios are specified by total equivalence among conditional item response probabilities, *full measurement invariance* is maintained across the Q groups. If $P(r_j|c, q) \neq P(r_j|c, q')$ for at least some indicator j , some latent class c , and groups q, q' , then there exists *partial measurement invariance*. That is, at least one group differs to some degree regarding the nature of at least one latent class. Any evidence of partial measurement invariance increases the ambiguity in interpreting differences in the latent class structure across the Q groups. Morin et al. (2016) unpacked the concept of partial measurement invariance within the multiple-group LPA framework into a sequence of six subtypes of invariance that could be assessed across groups. Figure 2.6 below illustrates the first four of Morin's MI subtypes.

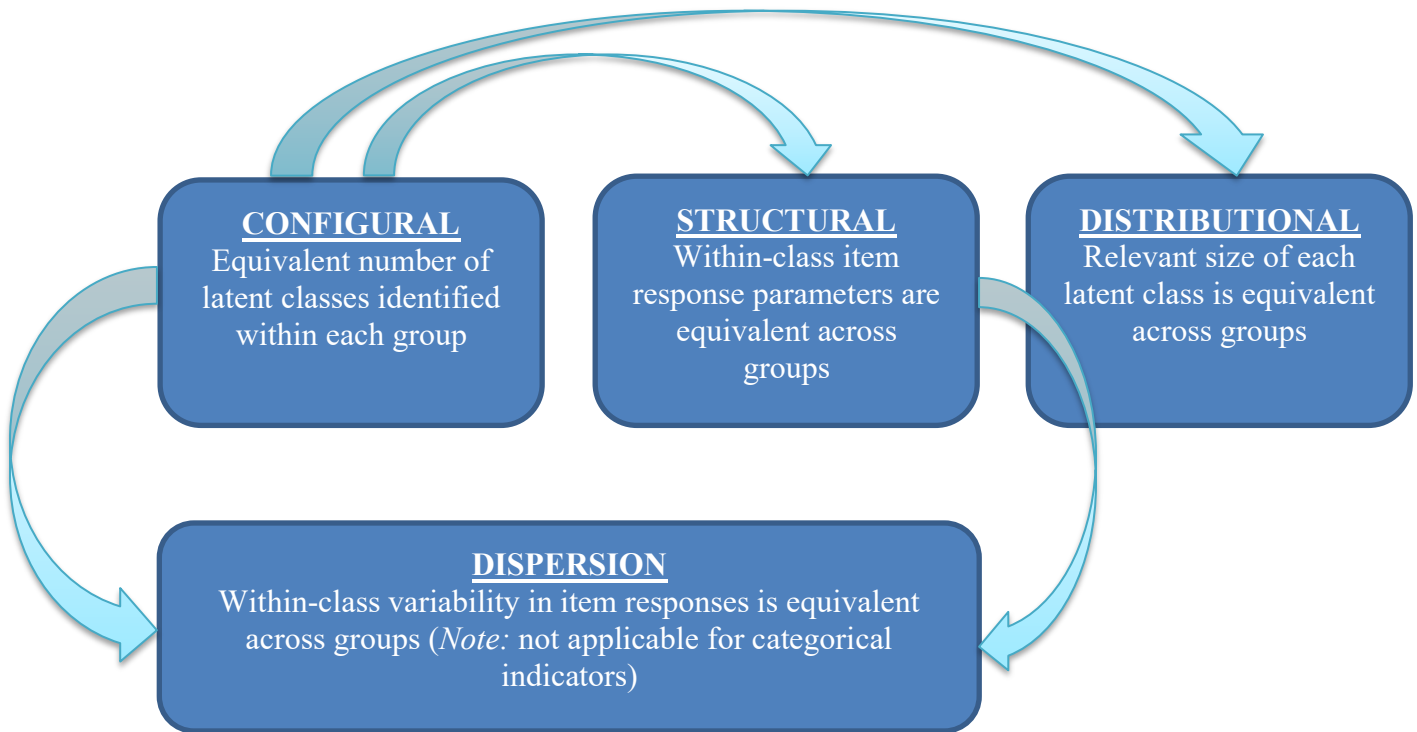


Figure 2.6. Sequence of testing for varying levels of measurement invariance across groups in a Latent Profile/Class Analysis framework, proposed by Morin, et al., 2016

Configural invariance is said to hold if the same *number* of latent classes emerge as the optimal solution across groups. Configural invariance is considered a logical prerequisite for the remaining three subtypes of invariance. For example, once configural invariance has been established, a researcher can test for equivalence of within-class item response parameters across groups (i.e., *structural* invariance). In the LPA framework, which derives latent classes from a set of continuously distributed indicators, structural invariance would require equating within-class item *means* across groups. For LCA

models with dichotomous predictors, for example, structural invariance would require that the within-class item-response *probabilities* are equivalent across groups.

Both configural and structural invariance are considered prerequisites for a third MI subtype, *dispersion* invariance, which is only applicable within an LPA framework. Dispersion invariance refers to the equivalence of within-class item *variability* parameters (i.e., interindividual differences) across groups. Variability parameters are not estimated for the categorical indicators from which latent classes in LCA are constructed, so dispersion invariance is not assessed in the LCA context. The fourth MI subtype, *distributional* invariance, calls for the equivalence in the relative *size* of each latent class across groups. Distributional invariance may be ignored in multiple-group LCA, as it is arguably substantively interesting to model differential distributions of latent class assignment across groups.

Beyond the four MI subtypes of configural, structural, dispersion, and distributional invariance, Morin et al. (2016) described the assessment of two additional types of invariance: *predictive* and *explanatory* invariance. Predictive invariance suggests that the relationships between latent class predictors and the classes themselves are equivalent across groups. A violation to predictive invariance might, therefore, provide evidence of a moderating effect of group membership on the relationship between a covariate and latent class membership. Explanatory invariance extends the concept of predictive invariance to the relationship between latent class membership and distal outcomes. While predictive and explanatory MI are not requirements for testing whether a latent class solution (i.e., measurement model) is equivalent across groups, they can

establish support for an estimated model's construct validity (Marsh et al., 2009; Morin et al., 2016). As such, these two subtypes of MI are not discussed further.

With regards to model estimation, the assessment and accommodation of partial invariance involves constraining some measurement parameters to equality across groups, but allowing others to be freely estimated (i.e., unconstrained). If the best-fitting model suggests that *all* class-specific item response probability parameters are unconstrained across groups, then the model is said to exhibit *full measurement non-invariance*. Further discussion on model estimation and the statistical assessment of measurement invariance is presented in later sections. First, the concept of across-group MI is extended to establishing MI across time points, and longitudinal measurement invariance within the LTA framework is introduced.

Longitudinal Measurement Invariance within the LTA Framework

Converting the measurement invariance expressions from the multiple-group LCA to instead reflect longitudinal measurement is relatively straightforward. Full measurement and structural equivalence across two time points is said to hold if the following conditions are met:

- $P(r_{jt}|c_t) = P(r_{jt-1}|c_{t-1})$, for all items j , latent classes c , and time points t , $t - 1$;
- $C_t = C_{t-1}$, for all time points t , $t - 1$; and
- $\gamma_{c_t} = \gamma_{c_{t-1}}$, for all latent classes c , and time points t , $t - 1$.

Again, the third requirement regarding latent class prevalence equivalence across time is not necessary for full longitudinal measurement invariance to hold and is often at odds with theoretical considerations. This is analogous to the concept of Morin et al.'s (2016) distributional MI presented earlier. The requirement for equivalence in the number of latent classes estimated at each time point is akin to configural invariance and is deemed a base requirement for other levels of structural invariance to hold. Full structural invariance for an *overall* LTA model would be met if 1) the class prevalence parameters were equivalent at each time point, and 2) the transition matrix took the form of an identity matrix (i.e., there is zero movement between classes across time points). However, such a restricted scenario, transition-wise, is not likely to be substantively interesting to researchers.

It follows that *partial* longitudinal measurement invariance in an LTA framework would exist if, for at least one indicator j and at least one latent class c , $P(r_{jt}|c_t) \neq P(r_{jt-1}|c_{t-1})$. This would mean that, to some degree, the interpretation of at least one of the latent classes differs between times t and $t - 1$. This is not an ideal characteristic to observe in data that are modeled by LTA, as the concept of growth/change in the latent classes across time points becomes much less straightforward. There are several ways partial measurement invariance could manifest in the LTA framework, given the large number of item-based parameters estimated by these models. This dissertation proposes to investigate the impact of only a few of the possible manifestations, which are presented in detail below.

Potential violations of LMI in the LTA framework

When estimating an LTA model, it is reasonable to expect configural invariance to hold (i.e., the same number of estimated latent classes are deemed optimal at each measurement occasion), yet a researcher may subsequently discover that only partial *structural* invariance is evident among the item-response parameters across time points. Reiterating from above, partial structural longitudinal invariance in the LTA framework would be evident if, after comparing the model fit of two nested LTA models, $P(r_{jt}|c_t) \neq P(r_{jt-1}|c_{t-1})$ for at least one indicator j and at least one latent class c in the “better fitting” model compared to the model wherein the parameter(s) is constrained to equality across measurement occasions.

Speaking broadly, partial LMI may cause a shift in homogeneity (i.e., the degree to which patterns of item responses are present within an estimated class) and/or latent class separation (i.e., the degree of differentiation among class-specific response patterns) across time. Drawing upon the adolescent delinquency example presented earlier in the chapter, a shift in latent class separation may be evident if, say, item-response probabilities were uniformly lower in the General Delinquents latent class when measured at a later point in time. Note that one could argue how this scenario also results in a shift in latent class homogeneity, since the particular response pattern $\mathbf{y} = (1,1,1,1,1,1)$ is now less definitive of the class of General Delinquents as a whole.

Tables 2.4 – 2.6 illustrate sets of item parameters from hypothetical LTA models extending the adolescent delinquency LCA to two time points, with evidence for varying degrees of partial LMI highlighted in bolded text. In Table 2.4 below, *TIME 2*:

SCENARIO A shows a uniform decrease in endorsing delinquent behavior among adolescents in the General Delinquents class from the first to second measurement occasions, slight increases in endorsing “lying to parents” by members of the Liars and Verbal Antagonists classes, and an increase in the probability of stealing items worth less than \$50 amongst members of the Shoplifters class. The researcher would still likely categorize the fifth latent class as “generally delinquent” at Time 2, but it appears that the rate of endorsing delinquent behaviors has declined a bit since the first measurement occasion. Combined with a selective increase in endorsing delinquent behaviors within a few other classes, one could reasonably deduce that the levels of latent class separation and homogeneity have diminished over time. What is *not* evident from the data, however, is the root cause(s) of these shifts (e.g., individuals in the General Delinquent class maturing over time; fewer environmental opportunities to engage in such behaviors; or perhaps changes in the operational definition of “lying to parents”), and possibly more importantly, whether this degree and/or type of partial LMI has an impact on the interpretation of the transitional probabilities estimated by the hypothetical model.

Table 2.4. Hypothetical LTA modeling five classes of youth delinquency over two time points, with longitudinal differences in latent class separation and homogeneity

	Latent Class				
	Non- delinquents	Liars	Verbal Antagonists	Shoplifters	General Delinquents
TIME 1					
<i>Latent class prevalences*</i>					
	.24	.27	.25	.13	.10
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.92
Damaged property	.00	.05	.25	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.07	.34	.17	.54
TIME 2, SCENARIO A: Uniform shift in within-class item-response parameters					
<i>Latent class prevalences*</i>					
	.25	.25	.22	.13	.15
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.82	.82	.74	.79
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.82
Damaged property	.00	.05	.25	.17	.58
Stolen something from store	.02	.02	.04	.92	.80
Stolen something worth < \$50	.00	.00	.06	.82	.75
Taken part in group fight	.03	.07	.34	.17	.44

*Latent class prevalences may not sum to 1.00 due to rounding.

Table 2.5 presents another hypothetical example of partial LMI within an LTA framework. In this scenario (i.e., *SCENARIO B*), there appears to be a marked decrease in the *proportion* of participants who are classified into the Shoplifters latent class. The within-class pattern of item response probabilities remains equivalent across

measurement occasions, but the probability of being assigned to that particular class has reduced from .13 to .05. It is likely that an LCA-specific assessment of model fit for this hypothetical example would have pointed towards a five-class solution at Time 1 and a four-class solution at Time 2. As will be discussed later in the chapter, some researchers prefer to assess LMI on the *overall* LTA model, choosing to force configural invariance on the number of classes at each time point simultaneously, which could result in the emergence of a sparsely populated latent class at Time 2, given distinct item-response patterns during Time 1.

The third hypothetical example, *SCENARIO C*, is very similar to *SCENARIO B* in that it illustrates a potential violation of configural invariance (see Table 2.6). Notice that when measured at Time 2, members of the second and third latent classes (known as Liars and Verbal Antagonists at Time 1) have begun to exhibit very similar patterns of item endorsement. Again, if class enumeration decisions were made separately at the LCA-level, a four-class solution may be optimal at Time 2, in which members of Time 1's Liars and Verbal Antagonists are better configured as one big homogeneous latent class. The resulting disparate number of extracted latent classes across time would violate the desired quality of configural invariance. Looking at it from another lens, latent class separation between the Liars and Verbal Antagonists becomes less distinct from Time 1 to Time 2.

Table 2.5. Hypothetical LTA modeling five classes of youth delinquency over two time points, with longitudinal differences in latent class prevalences

	Latent Class				
	Non- delinquents	Liars	Verbal Antagonists	Shoplifters	General Delinquents
TIME 1					
<i>Latent class prevalences*</i>					
	.24	.27	.25	.13	.10
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.92
Damaged property	.00	.05	.25	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.07	.34	.17	.54
TIME 2, SCENARIO B: Disappearance of one or more latent classes					
<i>Latent class prevalences*</i>					
	.26	.29	.28	.05	.12
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.92
Damaged property	.00	.05	.25	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.07	.34	.17	.54

*Latent class prevalences may not sum to 1.00 due to rounding.

Table 2.6. Hypothetical LTA modeling five classes of youth delinquency over two time points, with longitudinal shifts in latent class separation, homogeneity, and prevalences

	Latent Class				
	Non- delinquents	Liars	Verbal Antagonists	Shoplifters	General Delinquents
TIME 1					
<i>Latent class prevalences*</i>					
	.24	.27	.25	.13	.10
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.22	.89	.48	.92
Damaged property	.00	.05	.25	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.07	.34	.17	.54
TIME 2, SCENARIO C: Two latent classes merge into one					
<i>Latent class prevalences*</i>					
	.24	.27	.25	.13	.10
<i>Conditional item response probabilities of endorsement</i>					
Lied to parents	.00	.72	.72	.74	.89
Publicly loud/rowdy/unruly	.15	.60	.65	.48	.92
Damaged property	.00	.15	.18	.17	.68
Stolen something from store	.02	.02	.04	.92	.90
Stolen something worth < \$50	.00	.00	.06	.72	.85
Taken part in group fight	.03	.18	.29	.17	.54

*Latent class prevalences may not sum to 1.00 due to rounding.

Statistical Assessment of LMI Within an LTA Framework

Following the discussion of the hypothetical partial LMI examples above, a reader's intuition may have summoned the following questions: 1) *How* would I go about assessing LMI if I plan to model my longitudinal data within an LTA framework, and 2) *At what point in the process* should I implement the LMI assessment? The first question is more straightforward. Repeating an earlier section of the chapter: With regards to model estimation, the assessment and accommodation of partial invariance involves constraining some measurement parameters to equality across groups, but allowing others to be freely estimated (i.e., unconstrained). This allows for nested models to be compared on the same set of fit indices suggested for class enumeration decisions (e.g., BLRT, AIC, etc.). Indeed, the procedures for assessing LMI and coming to an optimal number of latent classes are somewhat intertwined in an LTA framework. *When* these procedures should be conducted is a less agreed-upon topic in the literature. A review of LTA-specific methodological research as well as applied research using LTA models seems to suggest a tendency towards two distinct options, based on differing views of when class enumeration decisions should be made. Figure 2.5 provides an overview of the most commonly observed methods of assessing within-class item response LMI in the LTA literature.

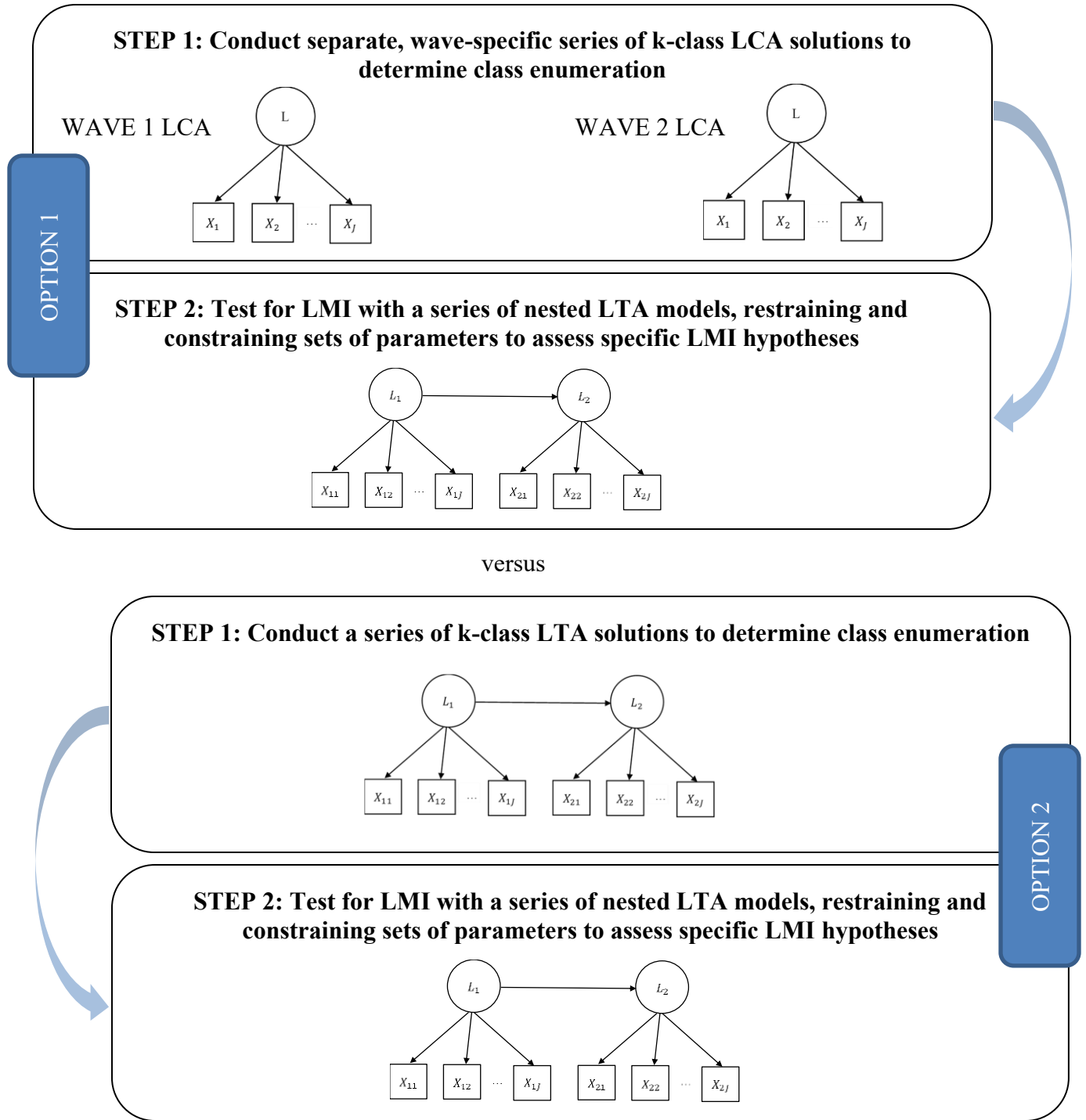


Figure 2.7. Two options for the sequence of class enumeration decisions and item response LMI assessment within an LTA framework with two time points

Researchers who implement option one (e.g., Muthén, Nylund-Gibson, et al.) prefer to make class enumeration decisions on the wave-specific LCA measurement models separately. A potential risk associated with this first step is encountering violations to configural invariance (i.e., the optimal solutions for each series of k -class models may yield different numbers of latent classes at each time point). This option treats the separate LCAs as more exploratory in nature. If the optimal solutions uncover differences in the number or type of latent classes at each time point, those differences should be considered for substantive merit and appropriately modeled in the subsequent tests for LMI at the LTA-level. However, decisions regarding which item parameters to fix/restrain may be made difficult if the underlying class configurations are not equivalent across time.

Researchers who implement option two (e.g., Bray, Collins, Lanza, etc.) consider the LTA to be the final determinant for class enumeration due to the ability to incorporate the autoregressive relationship between time points into the formation of the optimal latent classes. There appears to be a healthy mix of both options in the applied literature, though it is unusual for authors to go into explicit detail about their class enumeration and LMI procedures, particularly if parts of these procedures are exploratory in nature (e.g., separate LCAs). There are currently no published studies that directly compare these two procedures.

Impact of Misspecifying Invariance

“If it don’t fit, don’t force it.” – George Clinton

Whether the presence of partial LMI has an impact on LTA parameter estimation is currently unknown and is therefore the focus of the proposed dissertation. There have been a handful of simulation studies investigating LMI within the latent growth modeling (LGM) framework (Leite, 2007; Olivera-Aguilar, 2013; Wirth, 2008), which are described below.

Simulations Based on Latent Growth Modeling

Leite’s (2007) paper based on his dissertation research described simulated LMI conditions under strict factorial invariance, weak factorial invariance, and configural invariance under a multi-timepoint latent growth model. The strict factorial invariance condition ensured that the population factor loadings, error variances, and intercepts for each item were equivalent across measurement occasions, while weak factorial invariance conditions allowed the sets of population error variances and item intercepts to be randomly defined at each measurement occasion. In the configural invariance condition, separate sets of factor loadings, error variances, and item intercepts were randomly defined at each measurement occasion. Other manipulated conditions in Leite’s (2007) study included sample size, number of items per latent factor, item reliability, number of measurement occasions, and type of item equivalence (i.e., essentially tau-equivalent and essentially congeneric).

Leite (2007) then assessed the impact of combinations of the varying manipulated conditions on a set of overall model fit indices typically consulted in LGCA, including the CFI, the Tucker-Lewis Index (TLI), the root mean square error of approximation (RMSEA), and the chi-square statistic. Results indicated that under conditions of strict factorial invariance, most of the analysis iterations yielded fit index values that would correctly lead to the retention of the model. However, under configural invariance, the CFI and TLI indices produced Type II error rates surpassing 40%. The chi-square statistic was similarly biased, specifically in the positive direction. Interestingly, the magnitude of this positive bias increased with an increase in manipulated sample size. Positive bias in the chi-square statistic is desirable under these configural invariant conditions, as a researcher would thus be more likely to correctly reject the fit of a model that assumes LMI across measurement occasions.

In addition to assessing the impact of LMI on fit indices, Leite (2007) also looked at the impact on model parameter estimates, specifically the intercept and slope parameters, their respective variance/covariance parameters, and standard error estimates associated with those parameters. Under all manipulated conditions, Leite (2007) found the intercept parameter to be positively biased. Conversely, negative relative parameter bias was uncovered for the slope and variance/covariance parameters, particularly under essentially congeneric item conditions. Therefore, model-defined growth may be interpreted spuriously. The standard error estimates for the intercept, slope and variance/covariance parameters remained robust under all manipulated circumstances.

Wirth's dissertation (2008) also explored the effect of ignoring degrees of partial longitudinal measurement invariance within the LGM framework. Manipulated conditions in this simulation included sample size, type of item (i.e., regression-based factor scores versus constrained-covariance factor scores), time-adjacent factor correlations, linear versus free-loading growth, and seven levels of strict and partial LMI based on *systematic* change rather than randomly generated non-invariance [the latter design used in Leite's (2007) simulation]. Similar patterns of relative parameter bias were found by Wirth (2008) as were discussed in the summary of Leite's (2007) simulation above. Specifically, the slope parameter experienced the largest magnitude of bias compared to the intercept and variance parameters under varying degrees of partial LMI.

Olivera-Aguilar's (2013) dissertation extended the concepts behind both Leite's (2007) and Wirth's (2008) simulations to the autoregressive quasi-simplex modeling framework based on composite items (as compared to the traditional univariate LGM analysis). Manipulated study conditions included sample size, total number of items, the proportion of items with violations of invariance in the loadings or in the intercepts, and size differences across time in the loadings or in the intercepts. While Olivera-Aguilar (2013) discovered no impact of sample size on relative parameter bias, the LGM analyses yielded negatively biased slope parameters and variance components for the slope and intercept-slope covariance under all conditions of non-invariant item loadings. On the other hand, non-invariant intercepts resulted in positive bias in the slope parameter only. The AR model in Olivera-Aguilar's (2013) dissertation proved to be more robust in the face of violations to LMI. Only under the largest degree of non-invariant factor loadings

were significant levels of negative parameter bias detected. Non-invariant item intercepts had no impact on AR parameter estimation.

Simulations Based on Growth Mixture Modeling

Only one study to date has used Monte Carlo simulation methods to explore the impact of LMI in the GMM framework. A dissertation by Zhang (2015) extended the research by Leite (2007), Wirth (2008) and Olivera-Aguilar (2013). While the latter studies simulated longitudinal response data from one latent class, Zhang simulated data that were designed around multiple latent classes. Factors manipulated by Zhang (2015) included directional change in the non-invariant item intercepts, patterns of item loadings and item intercepts, percent of items containing a set of non-invariant item parameters, presence of time-adjacent within-item correlated measurement error, and latent class separation. Three separate GMMs were compared on parameter recovery/bias and class enumeration accuracy: a first-order GMM, a second-order GMM assuming measurement invariance, and a second-order GMM with freely estimated factor loadings and intercepts.

The third model cited above (second-order GMM with freely estimated parameters) was predictably far more robust to the varying degrees of violations to LMI than the other two GMM comparisons. Zhang (2015) found the first-order GMM to be incompatible with nearly all departures from LMI, while the accuracy of the second-order model that assumed invariance depended on patterns of “contamination level.” However, no universal or directional impact pattern emerged. Instead, different interactions of

manipulated conditions yielded rather different results; though, in general, greater bias and less precision in the slope parameter estimates were associated with greater departures from LMI.

STATEMENT OF PURPOSE

As discussed earlier, there is no current research that explores the impact of violations to assumptions of longitudinal measurement invariance on LTA parameter estimates when the model is incorrectly specified as maintaining measurement equivalence. Exhibiting substantively equivalent latent class measurement properties across time is thought to be critical for an unambiguous interpretation of both the latent classes themselves, as well as the probabilities of transitioning in and out of each latent class. Considered an integral prerequisite for LMI within the LTA framework, configural invariance holds when the same number of latent classes emerge as the best-fitting measurement solution at each time point.

A review of the literature suggests that several published studies employing LTA as a modeling framework contain clear evidence of various violations to configural LMI. For example, in their exploration of peer victimization and violence profiles across time, Felix, et al. (2018) estimate an LTA that regresses a *two*-class solution during college on a *four*-class solution during childhood, thus violating the basic assumption of configural invariance. Similarly, Chan and Wang (2018) present an LTA with differing numbers of latent classes across time in their research on college students' course-completion patterns. In perhaps a more subtle display of LMI violations, Ulbricht, et al. (2018) found that item-response parameters within one of their four classes of depression subtypes in men could not be reasonably confined to equality across measurement occasions, while structural equivalence held for the remaining three classes.

Researchers are finding LTA models to be a flexible, person-centered approach to modeling change in latent classes across time, and the prevalence of LTA-based published research is increasing in scope. It is imperative that researchers understand 1) the role that LMI plays in modeling a latent construct over time, 2) how to critically assess violations to LMI, and 3) the extent to which partial LMI can impact their study's results. A number of the "offending" studies referenced above provide a detailed account of the procedures they used to assess LMI, yet none comment on the potential limitations brought about by these violations. However, these studies at least acknowledge and model the configural non-invariance, allowing for a transparent substantive interpretation of changes to latent class structure over time. Had they forced an invariant model on their non-invariant data, the results would be (likely unknowingly) muddled by the impact of model misspecification.

It is unclear whether misspecifying any level of invariance in a model would be more damaging than allowing the non-invariance to flow through the model. There is very little research on LMI in LTA models, regarding either the nature of the presence of non-invariance or the impact of its suppression. The body of research regarding the impact of partial LMI in growth modeling has been primarily limited to LGMs (Leite, 2007; Olivera-Aguilar, 2013; Wirth, 2008). These studies are typically facilitated by simulating various factors (e.g., sample size, degree of LMI, number of items measured, etc.) and assessing the impact of combinations of those factors on various statistical outcomes (e.g., bias, model fit, variability in outcomes). To date, only one study has explored the impact of longitudinal measurement invariance within the GMM framework

(i.e., Zhang, 2015). However, Zhang's (2015) simulation focused specifically on latent class growth analyses (LCGA) and did not discuss LTA models.

Clearly, there is a lot of unexplored research territory regarding LMI within growth mixture modeling, and in particular, the LTA framework. The purpose of the current study is to initiate the exploration by focusing on the most basic level of LMI in latent transition analyses: configural invariance across measurement occasions. The research questions guiding the current study include the following:

- 1) If configural non-invariance is truly present in the data, how do the class enumeration decisions resolve in the overall LTA model when configural invariance is forced?*
- 2) What is the resulting impact on the estimated transition matrix?*

Recall that there are two common approaches to class enumeration in the LTA literature. One option is to conduct separate LCA measurement models to reach class enumeration decisions at each time point, then account for any configural non-invariance in the overall LTA model. The second option is to make final class enumeration decisions at the LTA level, inherently forcing configural invariance across time points. The proposed study intends to explore the impact of partial configural invariance on class enumeration decisions of the latter variety. Further, it is also of interest to measure the impact that partial configural invariance has on LTA parameter estimates – particularly the estimated transition matrix. Through the design of a set of Monte Carlo simulation studies, data exhibiting varying degrees of partial configural invariance will be generated as “true”

population conditions and fit against misspecified LTA models to assess the impact of forcing configural invariance. The goal is to provide applied researchers with an evidence-based “rule of thumb” for proceeding with class enumeration decisions when modeling their data in an LTA framework.

Chapter 3: Method

A two-part Monte Carlo simulation study will be conducted to investigate the impact of violations to assumptions of longitudinal measurement invariance (LMI) in latent transition analysis (LTA) models, specifically regarding configural invariance and class enumeration decisions.

SIMULATION STUDY DESIGN

The two simulation designs will be distinguished by their underlying pattern of partial configural invariance, as described below:

***Pattern A:** This design will include one latent class at Time 1 splitting into two latent classes at Time 2, specifically a three-class solution at Time 1 and a four-class solution at Time 2.*

***Pattern B:** This design will include two latent classes at Time 1 collapsing into one latent class at Time 2, specifically a four-class solution at Time 1 and a three-class solution at Time 2.*

Both patterns of configural non-invariance have been observed in the applied literature (Chan & Wang, 2018; Felix et al., 2018). It is reasonable to imagine a subset of one latent class altering their characteristic behaviors over time (e.g., response patterns) just enough to form a separate, homogenous latent class. Similarly, two separate latent classes may evolve over time to exhibit similar enough response patterns to warrant a decrease in the number of estimated classes.

In both simulated scenarios, the generated data will be designed around two measurement occasions, with five dichotomous indicators defining the latent class variable at each time point. Response patterns to the set of dichotomous indicators will be generated to produce different types and degrees of partial measurement invariance (specifically, configural invariance) between the LCA measurement models defined at each of the two time points.

Due to the scarcity of published methodological literature regarding handling LMI within an LTA framework, the rationale for the designs and parameters manipulated in the proposed simulation are influenced by studies on LMI in the general realm of growth mixture modeling (GMM).

Generating Conditions

Within each simulation design (i.e., Pattern A or Pattern B), a total of four conditions (i.e., factors) will be manipulated and fully crossed for a total of 90 conditions per design: class homogeneity/separation [well-defined classes (three conditions) versus poorly-defined classes (two conditions)], class prevalence splits between Time 1 and Time 2 in the non-invariant class (50/50, 60/40, 80/20), overall sample size (200, 500, 1000), and transition matrix design (ordered movement across classes versus non-ordered movement across classes).

Class homogeneity and separation

The concepts of latent class homogeneity and separation will be explored by generating “well-defined” and “poorly-defined” latent class models at each measurement

occasion. These concepts are particularly important in the interpretation of the estimated latent classes. Recall that homogeneity in latent classes can be evidenced by within-class item response probabilities close to 0 or 1, indicating high agreement among participants in each class. Latent classes that are highly separated will have within-class patterns of item responses that are highly endorsed within that particular class, but unlikely to be seen in other classes. Low class separation is not uncommon in the applied LTA literature, and is best illustrated when there is heavy overlap in item response probabilities across classes. While models with low latent class separation may have more “noise,” the overlap in class response patterns may be supported by substantive theory and therefore helpful in interpreting nuance among the classes.

Following the methodology presented by Baldwin (2015), the degree of homogeneity/separation will be determined by differing sets of logit threshold values associated with the within-class item response probabilities. Logits will be used instead of raw probabilities to facilitate simulating the LTA data in *Mplus*, via the transformation equation shown below:

$$p = \frac{1}{1 + \exp(\text{logit})}.$$

Negative logits correspond to probabilities greater than 0.50, while positive logits correspond to probabilities less than 0.50. In this simulation, the well-defined model will include logit thresholds of ± 1 , ± 2 , and ± 3 , which correspond to conditional probabilities

of .27/.73, .12/.88, and .05/.95, respectively. Note that the higher absolute value of the threshold equates to higher within-class agreement.

The poorly-defined models will be generated with accordingly lower latent class separation/homogeneity. As such, many items will be simulated to have conditional item probabilities near 0.50. Logit thresholds for these items will range from moderate to high. In the poorly-defined, but high logit threshold condition, increased overlap among class response patterns will be modeled to reflect low latent class separation. Due to the increase in within-class heterogeneity, it may be reasonable to expect more frequent model convergence issues among the poorly-defined models as compared to the well-defined models. Adjustments to the logit thresholds may be necessary to adequately explore the impact of latent class separation on LTA performance. Currently, the proposed set of manipulated logit thresholds is displayed in Table 3.1 below.

Table 3.1. Proposed logit thresholds for the well-defined and poorly-defined LTA models explored in this simulation

		Well-Defined Models			Poorly-Defined Models	
		Low Thresholds	Moderate Thresholds	High Thresholds	Moderate Thresholds	High Thresholds
Class 1	Item 1	1	2	3	-3	-2.5
	Item 2	1	2	3	0	-5
	Item 3	1	2	3	0	-1
	Item 4	1	2	3	0.4	2.5
	Item 5	1	2	3	0.85	2.5
Class 2	Item 1	1	2	3	0.85	1.5
	Item 2	1	2	3	3	1.5
	Item 3	-1	-2	-3	0.4	0
	Item 4	-1	-2	-3	0	-1
	Item 5	-1	-2	-3	-1	-5
Class 3	Item 1	-1	-2	-3	1.3	5
	Item 2	-1	-2	-3	0.4	1.5
	Item 3	-1	-2	-3	0.4	1
	Item 4	-1	-2	-3	4	-1
	Item 5	-1	-2	-3	0	0
Class 4	Item 1	-1	-2	-3	0	-1.5
	Item 2	-1	-2	-3	0.4	5
	Item 3	1	2	3	3	-5
	Item 4	1	2	3	1.3	5
	Item 5	1	2	3	1.3	5

Note. The presence of Class 4 at either of the two simulated measurement occasions will be dependent on the simulation's non-invariance pattern (i.e., Pattern A or Pattern B).

Class prevalence splits between Time 1 and Time 2 in non-invariant class

Class prevalence parameters will be equal within and across time periods in the invariant classes and manipulated in the non-invariant class, specifically by how the class splits/merges across time. In the 3-class to 4-class simulation design (i.e., Pattern A), the three classes will be evenly distributed at Time 1 (i.e., .33, .33, .34), and the additional class at Time 2 will be generated from the following splintering patterns in one of the

three Time 1 classes: 50/50, 60/40, and 80/20. Specifically, a 50/50 split will model half of Class 3 transitioning to Class 4, which is designed as the most dramatic split. In the 60/40 and 80/20 conditions, respectively, 40% and 20% of Class 3 members will transition to Class 4 at Time 2. In the 4-class to 3-class simulation, the pattern is reversed. That is, the three classes at Time 2 will be evenly dispersed (i.e., .33, .33, .34), and the two “collapsing” classes in Time 1 will be generated with the same pattern as above (i.e., 50/50, 60/40, 80/20).

Overall sample size

Maintaining a necessary overall sample size is of great importance to researchers using latent variable models as it is a requirement for ensuring adequate power of the model. Sample size recommendations in the literature are varied: Muthén and Muthén (2002) suggest a rule of thumb of five to ten observations per model-estimated parameter, others recommend at least 50 observations per variable, and a yet broader suggestion calls for at least 100 observations total. In sum, there are no clear-cut guidelines that can be applied to all modeling conditions.

In each simulation within this dissertation, the overall sample size will be generated at three levels: 200, 500, and 1,000 individual “respondents.” This mimics the manipulated sample size conditions within the Nylund et al. (2007) simulation regarding class enumeration decisions within LCA and GMM frameworks, and also approaches the extreme low end of the suggested sample size ranges for LTA (Lanza et al., 2003).

Transition matrix design

Two transition probability matrices will be simulated in this study. The first matrix will force strict forward movement (i.e., ordered movement) among the latent classes from Time 1 to Time 2. The second will allow for unordered movement among latent classes across measurement occasions. Tables 3.2 and 3.3 below present proposed transition probabilities for both matrix simulations.

Table 3.2. Proposed transition probability matrices representing ordered movement between classes

		Time 2			
		Class 1	Class 2	Class 3	Class 4
Time 1	Class 1	0.80	0.15	0.04	0.01
	Class 2	0.00	0.85	0.13	0.02
	Class 3	0.00	0.00	***	***

		Time 2		
		Class 1	Class 2	Class 3
Time 1	Class 1	0.85	0.13	0.02
	Class 2	0.00	0.90	0.10
	Class 3	0.00	0.00	1.00
	Class 4	0.00	0.00	1.00

*Transition probabilities marked with '***' will be dependent on the varying conditions of class prevalence splits between Time 1 and Time 2 for the non-invariant class.*

Table 3.3. Proposed transition probability matrices representing unordered movement between classes

		Time 2			
		Class 1	Class 2	Class 3	Class 4
Time 1	Class 1	0.80	0.15	0.04	0.01
	Class 2	0.02	0.85	0.11	0.02
	Class 3	0.04	0.05	***	***
		Time 2			
		Class 1	Class 2	Class 3	
Time 1	Class 1	0.85	0.13	0.02	
	Class 2	0.10	0.80	0.10	
	Class 3	0.04	0.05	0.91	
	Class 4	0.03	0.02	0.95	

*Transition probabilities marked with '***' will be dependent on the varying conditions of class prevalence splits between Time 1 and Time 2 for the non-invariant class.*

Data Generation and Estimation

For each of the 90 combinations of manipulated study conditions within each of the two simulations, 500 datasets will be generated for a total of 45,000 datasets. The data will be generated in *Mplus* via the *MplusAutomation* package in R and analyzed in SAS 9.4, following the procedures outlined below (Hallquist & Wiley, 2018).

Generating models

Raw data for all of the simulated datasets will be generated under multivariate normality according to the specified sample size, class heterogeneity, class prevalence, and transition matrix conditions mentioned previously. These data will be designed to conform to an LTA measured at two time points, as per the fundamental equation discussed in Chapter 2:

$$P(Y = \mathbf{y}) = \sum_{c_1=1}^C \sum_{c_2=1}^C \gamma_{c_1} \tau_{c_2|c_1} \prod_{t=1}^2 \prod_{j=1}^J \rho_{r_{j,t}|c_t}$$

As such, the data will be generated as probability vectors for each simulated subject. Each of the two simulation designs (i.e., Pattern A and Pattern B) are based on measurement models indicated by a finite number of items with a finite number of response options, thus yielding a finite number of overall response patterns. Recall the discussion of the contingency table $W = \prod_{j=1}^J R_j$ in Chapter 2, in which each cell represents a unique pattern of item responses. Each possible response pattern will be associated with a cumulative probability vector derived from model specifications, and subjects will be assigned to a probability vector based on random assignment.

Data Analysis

All simulated datasets will be analyzed within *Mplus*, by way of a series of k -class LTA models to first explore class enumeration decisions. Because the focus of this dissertation is on the effects of mis-specified configural invariance, class enumeration decisions will be made at the overall LTA level. That is, separate wave-specific LCA models will not be used to capture the best-fitting measurement model. γ , τ , and ρ parameters will be estimated by each LTA model and compared to the generated values for the population. The default estimator used for mixture models in *Mplus* is Maximum Likelihood with robust standard errors (MLR).

Class Enumeration Decisions

Class enumeration will be determined by a collection of information criteria, as discussed earlier in Chapter 2 (i.e., AIC, BIC, CAIC, and ABIC, specifically). While BLRT and LMR-LRT have been identified as performing well for LCA class enumeration decisions, the efficacy of these alternative likelihood ratio difference tests has yet to be studied for LTA (Ryoo et al., 2018). Further, researchers presenting class enumeration decisions at the LTA level within the applied literature tend to rely only on information criteria, so a similar method will be demonstrated in this study. The “favored” number of classes identified by each fit index will be recorded and summarized. Because simulations in Pattern A and Pattern B are designed to reflect configural non-invariance via disparate numbers of latent classes measured at each time point, the best-fitting LTA model determined by the set of fit indices will always be technically incorrect. One question this dissertation hopes to address is whether class enumeration decisions made at the overall LTA level favor the larger or smaller number of wave-specific latent classes, assuming they truly differ in number. While there appears to be no uniformly suggested threshold for correct class enumeration rates defined in the literature, these rates will be compared to the traditional cutoff for adequate statistical power, 0.80.

Statistical Properties

This simulation study also intends to assess how accurately the best-fitting model captures the true (i.e., generated) parameter values. This is accomplished by examining

the calculated relative parameter bias and the relative standard error bias for model parameters of interest. Model convergence rates will also be calculated and discussed.

Relative Parameter Bias

An estimator is said to be unbiased when the expected value of the distribution of estimates is equal to the parameter estimated (i.e., $E(\hat{\theta}) = \theta$; Wackerly, Mendenhall, & Scheaffer, 1996). According to this definition, relative parameter bias is calculated as follows:

$$B(\hat{\theta}_i) = \frac{\bar{\hat{\theta}}_i - \theta_i}{\theta_i}$$

where θ_i is the population value of parameter i and $\bar{\hat{\theta}}_i$ is the parameter estimate averaged across the 500 replications in each condition. According to Hoogland and Boomsma (1998), absolute values of relative parameter bias less than a magnitude of 0.05 is considered acceptable. Muthén and Muthén (2002) state that relative parameter bias should not exceed 0.10 in their guidance for conducting Monte Carlo simulation studies.

Relative Standard Error Bias

Accuracy of the standard errors will be calculated in a similar manner. Given the average of the estimated standard errors for the i th parameter, $\bar{\hat{s}}_{\theta_i}$, and the empirical standard error for the i th parameter, \hat{s}_{θ_i} , (representing the standard deviation of the $\hat{\theta}_i$ s), relative standard error bias (RSEB) will be calculated using the following:

$$B(\hat{s}_{\theta_i}) = \frac{\bar{\hat{s}}_{\theta_i} - \hat{s}_{\theta_i}}{\hat{s}_{\theta_i}},$$

and assessed against Hoogland and Boomsma's stated threshold for substantial standard error bias (absolute values of RSEB exceeding 0.10).

To further identify the source(s) of both parameter and standard error bias, a series of analyses of variance (ANOVAs) will be estimated. Two-way interactions among the study factors will be included in the analyses for a more detailed exploration of the source(s) of bias. However, the full factorial ANOVA is excluded from the current study to ease interpretation and because the main effects of study factors are hypothesized to be the most impactful on LTA parameter recovery. A minimum cutoff value of 0.06 will be used as a criterion for practical significance for the estimated partial η^2 (Anderson & Gerbing, 1984; Cohen, 1988).

Chapter 4: Results

This chapter begins with an overview of the key procedural elements that were involved in the simulation study. A summary of modeling-specific topics follows (i.e., convergence rates and class label switching). Finally, the results from the simulation study are presented in detail. Where applicable, the reader is directed to specific Appendix tables that provide a more granular lens for interpreting the results.

SIMULATION PROCEDURE

The MplusAutomation package in R Studio was critical for efficiently building the individual *Mplus* input files. Only 15 template files were necessary to create the 720 input files required for the simulation (i.e., $720 = 180$ combinations of conditions, run for two- through five-class model specifications). An example template file is included in Appendix C, named “LTA_RB1_taus_template.inp”, which was used to write a large collection of *Mplus* input files to a working directory by simply executing the following command in the MplusAutomation R package:

```
createModels(“LTA_RB1_taus_template.inp”)
```

One of the input files created by the command above is also included in Appendix C (“LTA_200_RB1_5050_TB1_5c.inp”). Batch running the set of created input files within the *Mplus* system is also accomplished via MplusAutomation, by executing a *runModels* command that specifies the directory location of the input files. R and *Mplus* then communicate with each other to sequentially run all input files in the specified location,

without the need for user input. Running all 720 LTA programs took two machines approximately two total days to run, with computing time increasing as the number of classes estimated increased.

Each of the 720 programs produced an *Mplus* output file and a csv file containing model results for all replications that converged. Due to the highly parameterized nature of the models and the forced configural invariance on non-invariant data, model convergence issues were expected. In earlier experimental runs using *Mplus*'s default settings, model convergence rates were unacceptably low. *Mplus* output is designed to provide detailed feedback and possible solutions for non-convergence issues, and the most commonly proposed fix entailed increasing both the number of random starts (STARTS=) and the number of iterations for the EM algorithm (MITERATIONS=) to prevent models that yield multiple local maxima (Asparouhov & Muthén, 2019). While adjusting these model specifications resulted in a significant increase in computing time, convergence rates rose to levels that were far more accommodating for robust analysis. A detailed summary of convergence rates is provided in the subsequent section.

The 720 resulting csv files were imported into SAS and appended into separate k -class datasets for $k = 2, 3, 4, 5$ class solutions, as each k -class model estimates a different number of parameters. These datasets were investigated for peculiarities such as fixed standard errors and evidence of class label switching. The latter is an issue that frequently surfaces in *Mplus* when specifying non-zero random starts, adding a level of difficulty to the process of summarizing class-specific estimates across replications in a simulation study. Class label switching will be discussed in more detail in a later section. Finally,

after reaching a tolerably “clean” set of k -class results datasets, model statistics were aggregated across replications for each of the 720 models run.

CONVERGENCE RATES

As mentioned earlier, once the ideal STARTS and ITERATIONS had been specified, model convergence rates began to stabilize at an acceptable level. Tables 4.1 through 4.4 provide model-specific convergence rates for the 180 LTA models run in this study, estimated for two- through five-class solutions.⁶ For the set of 500 replications run for each model, the two-class models had the highest convergence rates out of the 2-, 3-, 4-, and 5-class model families. Ninety-one percent of the 180 two-class models had 100% convergence rates (see Table 4.1). The lowest convergence rates seen among the two-class models were predominantly associated with the Poorly-Defined, Moderate Thresholds class separation condition, although the lowest convergence rate is still quite high at 98%.

⁶ Beginning in this chapter, tables of results are frequently shown with a color gradient applied to cell values. Please note that this color gradient is merely a visual tool to illustrate the range of cell values within a table and does not signify statistical or practical significance.

Table 4.1. Model Convergence Rates, Two-Class Solutions

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	1.000	1.000	1.000	0.996	1.000
			500	1.000	1.000	1.000	0.998	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		60/40	200	1.000	1.000	1.000	1.000	1.000
			500	1.000	1.000	1.000	0.998	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		80/20	200	1.000	1.000	1.000	1.000	1.000
			500	1.000	1.000	1.000	0.996	1.000
			1000	1.000	1.000	1.000	0.984	1.000
	Unordered	50/50	200	0.998	1.000	1.000	0.996	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	0.998	1.000
		60/40	200	1.000	1.000	1.000	1.000	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		80/20	200	0.998	1.000	1.000	0.998	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	0.994	1.000
B	Ordered	50/50	200	1.000	1.000	1.000	0.996	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		60/40	200	1.000	1.000	1.000	0.998	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		80/20	200	1.000	1.000	1.000	0.998	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000
	Unordered	50/50	200	1.000	1.000	1.000	0.998	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		60/40	200	1.000	1.000	1.000	1.000	1.000
			500	1.000	1.000	1.000	0.998	1.000
			1000	1.000	1.000	1.000	1.000	1.000
		80/20	200	1.000	1.000	1.000	0.998	1.000
			500	1.000	1.000	1.000	1.000	1.000
			1000	1.000	1.000	1.000	1.000	1.000

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Convergence rates for the three-class models ranged from 82% to 100%, and the lowest rates are mostly confined to the Poorly-Defined, High Threshold class separation group, though minor dips in convergence are scattered throughout models with LMI Pattern A (see Table 4.2). As more classes are added to the estimation models, an increase in model complexity naturally follows. Highly parameterized models are less likely to converge and this is seen in Tables 4.3 and 4.4, which present the range of convergence rates for four-class and five-class models, respectively (i.e., 58% to 100% within four-class models and 54% to 98% within five-class models).

Convergence rates for four-class models tend to be lower as sample sizes decrease, as would be expected. The class separation conditions with high thresholds have slightly lower convergence rates than the other class separation conditions, particularly within the LMI Pattern A group (i.e., the third latent class at Time 1 splits into two latent classes at Time 2). Further, most of the lowest rates for four-class models appear within the LMI Pattern A group. Since the great majority of parameters estimated by these LTA models are for the Time 1 latent classes (i.e., all item response and class prevalence parameters), it is possible that forcing the parameterization of a non-existent fourth latent class at Time 1 is more likely to thwart the optimization process compared to the Pattern B models, for which the fourth latent class at Time 1 is provided in the generated data. This relationship between convergence rates and LMI pattern is less evident in the five-class models.

Table 4.2. Model Convergence Rates, Three-Class Solutions

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.998	0.992	0.992	1.000	0.826
			500	0.994	1.000	1.000	1.000	0.894
			1000	0.990	1.000	1.000	0.996	0.966
		60/40	200	0.996	1.000	1.000	0.996	0.888
			500	0.992	1.000	1.000	1.000	0.934
			1000	0.996	1.000	1.000	1.000	0.968
		80/20	200	0.994	0.928	0.862	1.000	0.834
			500	0.996	0.988	0.920	0.998	0.878
			1000	1.000	0.996	0.950	0.992	0.966
	Unordered	50/50	200	0.998	0.996	0.998	0.996	0.846
			500	0.994	1.000	1.000	0.998	0.934
			1000	0.996	1.000	1.000	1.000	0.960
		60/40	200	1.000	1.000	1.000	1.000	0.948
			500	0.988	1.000	1.000	0.996	0.960
			1000	0.982	1.000	1.000	0.998	0.982
		80/20	200	0.992	0.960	0.960	1.000	0.824
			500	0.998	0.992	0.968	0.994	0.912
			1000	0.996	0.998	0.986	0.984	0.968
B	Ordered	50/50	200	0.994	1.000	1.000	1.000	0.998
			500	0.994	1.000	1.000	0.998	0.998
			1000	0.982	1.000	1.000	1.000	1.000
		60/40	200	0.998	1.000	1.000	1.000	0.994
			500	0.988	1.000	1.000	0.998	0.998
			1000	0.978	1.000	1.000	1.000	1.000
		80/20	200	0.994	1.000	1.000	1.000	0.992
			500	0.986	1.000	1.000	0.998	0.998
			1000	0.954	1.000	1.000	1.000	1.000
	Unordered	50/50	200	1.000	1.000	1.000	0.998	1.000
			500	0.990	1.000	1.000	0.998	1.000
			1000	0.980	1.000	1.000	1.000	1.000
		60/40	200	1.000	1.000	1.000	0.998	0.994
			500	0.990	1.000	1.000	0.998	1.000
			1000	0.980	1.000	1.000	0.996	1.000
		80/20	200	0.996	1.000	1.000	0.994	0.922
			500	0.990	1.000	1.000	1.000	1.000
			1000	0.968	1.000	1.000	0.998	1.000

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.3. Model Convergence Rates, Four-Class Solutions

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.934	0.820	0.578	0.930	0.596
			500	0.950	0.916	0.806	0.954	0.772
			1000	0.948	0.956	0.882	0.970	0.856
		60/40	200	0.956	0.856	0.584	0.954	0.602
			500	0.958	0.892	0.796	0.982	0.704
			1000	0.972	0.940	0.902	0.980	0.858
		80/20	200	0.884	0.776	0.648	0.904	0.660
			500	0.936	0.882	0.778	0.960	0.822
			1000	0.946	0.948	0.838	0.968	0.864
	Unordered	50/50	200	0.956	0.846	0.626	0.964	0.598
			500	0.948	0.940	0.864	0.978	0.794
			1000	0.968	0.984	0.952	0.972	0.908
		60/40	200	0.954	0.908	0.712	0.952	0.672
			500	0.988	0.960	0.860	0.980	0.778
			1000	0.990	0.976	0.958	0.994	0.890
		80/20	200	0.896	0.804	0.624	0.924	0.662
			500	0.936	0.934	0.826	0.978	0.826
			1000	0.954	0.958	0.894	0.972	0.912
B	Ordered	50/50	200	0.894	0.978	0.890	0.932	0.970
			500	0.914	0.964	0.998	0.930	0.996
			1000	0.938	0.968	0.996	0.932	0.998
		60/40	200	0.902	0.974	0.864	0.950	0.972
			500	0.910	0.960	0.998	0.946	0.992
			1000	0.942	0.956	0.996	0.952	0.996
		80/20	200	0.936	0.962	0.758	0.938	0.930
			500	0.932	0.970	0.988	0.952	0.992
			1000	0.948	0.984	0.996	0.966	0.996
	Unordered	50/50	200	0.930	0.990	0.972	0.946	0.974
			500	0.960	0.988	1.000	0.966	0.996
			1000	0.984	0.996	1.000	0.978	0.994
		60/40	200	0.938	0.984	0.942	0.946	0.970
			500	0.976	0.992	0.998	0.980	0.994
			1000	0.978	1.000	1.000	0.982	0.996
		80/20	200	0.946	0.966	0.850	0.966	0.952
			500	0.972	0.988	0.990	0.970	0.990
			1000	0.974	0.990	1.000	0.984	0.996

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.4. Model Convergence Rates, Five-Class Solutions

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.890	0.880	0.554	0.850	0.690
			500	0.924	0.906	0.614	0.922	0.800
			1000	0.956	0.900	0.706	0.940	0.884
		60/40	200	0.906	0.852	0.576	0.882	0.714
			500	0.926	0.916	0.588	0.924	0.784
			1000	0.952	0.900	0.712	0.952	0.888
		80/20	200	0.890	0.842	0.538	0.830	0.654
			500	0.922	0.848	0.592	0.922	0.744
			1000	0.926	0.880	0.716	0.954	0.806
	Unordered	50/50	200	0.896	0.882	0.592	0.874	0.712
			500	0.932	0.902	0.690	0.932	0.824
			1000	0.954	0.924	0.756	0.980	0.888
		60/40	200	0.890	0.882	0.628	0.840	0.776
			500	0.962	0.868	0.674	0.934	0.832
			1000	0.962	0.936	0.740	0.982	0.858
		80/20	200	0.894	0.878	0.558	0.866	0.690
			500	0.950	0.862	0.676	0.922	0.810
			1000	0.946	0.910	0.706	0.970	0.826
B	Ordered	50/50	200	0.878	0.944	0.578	0.864	0.814
			500	0.904	0.894	0.894	0.896	0.848
			1000	0.948	0.906	0.916	0.944	0.852
		60/40	200	0.876	0.930	0.544	0.894	0.808
			500	0.900	0.880	0.898	0.902	0.862
			1000	0.944	0.916	0.924	0.942	0.854
		80/20	200	0.896	0.880	0.570	0.864	0.778
			500	0.922	0.878	0.850	0.940	0.850
			1000	0.936	0.918	0.924	0.934	0.842
	Unordered	50/50	200	0.892	0.918	0.654	0.898	0.812
			500	0.916	0.866	0.888	0.940	0.866
			1000	0.960	0.876	0.820	0.944	0.828
		60/40	200	0.900	0.914	0.610	0.886	0.812
			500	0.918	0.866	0.892	0.938	0.848
			1000	0.958	0.880	0.834	0.960	0.848
		80/20	200	0.908	0.890	0.568	0.896	0.788
			500	0.936	0.872	0.836	0.958	0.828
			1000	0.942	0.890	0.876	0.946	0.844

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.4 shows that the Well-Defined, High Thresholds class separation condition appears to have the largest negative impact on convergence rates, particularly at lower sample sizes. While this was not a predicted result, per se, it makes sense that a model that misspecifies the number of latent classes would have the hardest time optimizing on class data that are designed for maximum separation and within-class homogeneity.

CLASS ENUMERATION RESULTS

The penalized-likelihood information criteria AIC, BIC, CAIC, and ABIC were each considered for determining the optimal number of latent classes for each LTA model run. Two methods for aggregating IC-based solutions across model replications were explored:

1. Using the “average IC” method, values for each of the four information criteria (IC) were averaged across converged replications and subsequently compared across the k -class models. Class enumeration decisions were made for each IC for performance comparisons, with the k -class model having the lowest average IC value identified as the best-fitting solution for that particular model.
2. Using the “proportion of replications” method, class enumeration decisions are made at the replication level. The lowest value of an IC across the k -class solutions within one model replication is selected as the best-fitting solution. The proportions of k -class solutions across the

converged replications are compared, and the solution tied to the majority (or plurality) of replications is deemed the overall best-fitting for that model.

These two methods showed near-perfect agreement, with the replication-based method selecting a less complex solution in three or fewer of the 180 model combinations for each IC comparison. Results for the replication-based method are presented in Appendix D.

Tables 4.5 through 4.8 provide the class enumeration results for AIC, BIC, CAIC, and ABIC, respectively. It is helpful to remember that none of these best-fitting solutions are “correct,” since all of the underlying datasets are generated with different numbers of latent classes at each time point. Indeed, it may be presumptuous to state whether the three- or four-class model is the *preferred* misspecified solution for a specific set of generated conditions. The four-class solution may facilitate a more flexible interpretation of the non-invariant class split/merge, given the extra class estimated at one of the two time points. However, the three-class model may provide a conveniently more parsimonious view of data in which the generated non-invariance is particularly ill-defined (e.g., low class separation, small splits in the non-invariant class over time). This section is therefore an informal exploration into the repercussions of forcing longitudinal configural invariance on a non-invariant reality.

While the BIC and CAIC are often chosen as preferred fit indices for class enumeration decisions in cross-sectional mixture models (e.g., LCA; Nylund et al., 2007), they did not perform as well as expected in the current simulation (see Tables 4.6

and 4.7), perhaps due to the added model complexity introduced by the autoregressive framework. Of the four indices compared, BIC and CAIC yielded the most variability in class solutions and were the only indices to select best-fitting two-class solutions. These results are somewhat aligned with other simulation studies that show BIC and CAIC tending to underfit or choose an overly simplistic solution compared to AIC when the models are highly parameterized (Dias, 2006; Dziak et al., 2020; Lin & Dayton, 1997). Indeed, Dias (2006) found that the risk of underfitting increased when the latent classes' response patterns were less distinct (i.e., lower class separation). The literature also suggests that AIC and ABIC may be more likely than BIC and CAIC to select the correct number of classes in more complex structural situations (Lin & Dayton, 1997), which seems to be demonstrated in the current study.

Table 4.5. Class Enumeration Decisions, AIC

Class Separation (via item response parameter patterns)								
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	4c*	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c
		80/20	200	4c	4c	4c	4c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
	Unordered	50/50	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	4c	4c	4c	4c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
B	Ordered	50/50	200	4c*	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		80/20	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c
	Unordered	50/50	200	4c*	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
		80/20	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Cells with an asterisk indicate that the majority or plurality of replication-based class enumeration solutions yield a different best-fitting solution (3 classes rather than 4).

Table 4.6. Class Enumeration Decisions, BIC

Class Separation (via item response parameter patterns)								
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	4c*	4c	4c	3c	4c
		60/40	200	2c	3c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	4c	4c	2c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
	Unordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	3c	4c*	2c	2c
			500	2c	3c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	4c	4c	2c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
B	Ordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	3c	4c	2c	2c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
	Unordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	3c	4c	2c	2c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Cells with an asterisk indicate that the majority or plurality of replication-based class enumeration solutions yield a different best-fitting solution (3 classes rather than 4).

Table 4.7. Class Enumeration Decisions, CAIC

Class Separation (via item response parameter patterns)								
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	3c	4c	2c	3c*
			500	2c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	4c	4c	2c	4c
			500	3c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
	Unordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	3c	3c	2c	2c
			500	2c	3c	4c	3c	3c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	4c	4c	2c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	4c	4c
B	Ordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	3c	4c	2c	2c
			500	2c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
	Unordered	50/50	200	2c	4c	4c	2c	3c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		60/40	200	2c	4c	4c	2c	3c
			500	2c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	2c	3c	4c	2c	2c
			500	2c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Cells with an asterisk indicate that the majority or plurality of replication-based class enumeration solutions yield a different best-fitting solution (2 classes rather than 3).

Table 4.8. Class Enumeration Decisions, ABIC

Class Separation (via item response parameter patterns)								
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	3c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	4c	4c	4c	4c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
	Unordered	50/50	200	3c	4c	4c	3c	4c
			500	4c*	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
		80/20	200	4c	4c	4c	4c	4c
			500	4c	4c	4c	4c	4c
			1000	4c	4c	4c	4c	4c
B	Ordered	50/50	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	3c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c
		80/20	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c
	Unordered	50/50	200	3c	4c	4c	3c	4c
			500	4c	4c	4c	3c	4c
			1000	4c	4c	4c	4c	4c
		60/40	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	4c	4c	4c	3c	4c
		80/20	200	3c	4c	4c	3c	4c
			500	3c	4c	4c	3c	4c
			1000	3c	4c	4c	3c	4c

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Cells with an asterisk indicate that the majority or plurality of replication-based class enumeration solutions yield a different best-fitting solution (3 classes rather than 4).

Both AIC and ABIC preferred a four-class solution across all iterations of the Well-Defined, Moderate Thresholds; Well-Defined, High Thresholds; and Poorly-Defined, High Thresholds class separation conditions (see Tables 4.5 and 4.8). BIC uniformly selected a four-class solution for all models under the Well-Defined, High Thresholds condition, and CAIC selected a four-class solution in all but one iteration of the Well-Defined, High Thresholds condition. For the remaining class separation conditions, AIC tended to favor four-class solutions for the Well-Defined, Low Thresholds group—particularly when generated with larger sample sizes—and was equally likely to choose either three- or four-class solutions for the Poorly-Defined, Moderate Thresholds group. ABIC, on the other hand, was slightly more likely to yield a three-class solution for the Well-Defined, Low Thresholds and Poorly-Defined, Moderate Threshold conditions.

Interestingly, and a bit unexpectedly, both AIC and ABIC uniformly recommended a four-class solution for the models based on the least dramatic split from three to four classes (i.e., LMI Pattern A, 80/20 split; meaning that only 20% of Time 1 Class 3 broke off into their own class at Time 2), regardless of sample size, class separation, or transition pattern. When considering only the magnitude of class prevalence splitting, it seems intuitive to predict a larger split in Class 3 as being more likely to elicit an overfit four-class solution (overfit at Time 1, that is) than a situation where only a small proportion of Class 3 becomes independent. However, under Well-Defined, Low Thresholds and Poorly-Defined, Moderate Thresholds, both the largest (50/50) and smallest (80/20) split scenarios were far more likely to yield a best-fitting

four-class solution than the less extreme split (60/40), which almost exclusively resulted in three-class solutions with both AIC and ABIC selection. It would be interesting to explore the details of this relationship using more nuanced levels of class prevalence splits, within-class homogeneity, and across-class separation.

Both the three- and four-class solution sets are included in subsequent analyses of accuracy and consistency in LTA parameter estimation. The two-class models are less likely to be selected by empirical researchers facing data with similarly non-invariant properties, from both an information criteria selection lens and a substantive interpretation lens.

CLASS LABEL SWITCHING

When estimating a latent variable mixture model, either a singular model or multiple replications for a simulation study, it is a common issue for the resulting sets of class-specific parameter estimates to appear in a different order than what was imposed in the model syntax. Further, when running multiple permutations of the same model for a simulation, this “class label switching” phenomenon is likely to differ at the replication level, which produces an obvious obstacle for aggregating individual parameter estimates across the set of replications. Label switching in finite mixture modeling is due to the arbitrary ordering of latent classes in the estimation procedure (Cho et al., 2010; Chung et al., 2008; Tueller et al., 2011). For example, generated Classes 1, 2, 3, and 4 may receive labels of 2, 3, 4, 1 in the model output, according to, say, the estimated item response parameters. As parameter estimation is influenced by a multitude of modeling conditions,

some instances of label switching may be less obvious than others due to estimated values that are substantially different from the population parameter.

It is imperative that instances of class switching in latent variable mixture modeling simulations are identified and corrected before summarizing results.⁷ Upon visual inspection of the current simulation's output datasets, it was very clear that label switching was going to be an issue. Several detection and prevention methods have been proposed in the literature—for example, fixing the number of random starts to zero is a common preventative measure cited in the *Mplus* users' forums. However, the generated and estimated conditions for this simulation necessitated an *increase* in the number of random starts from the default values provided by *Mplus*. Specifying “STARTS = 0” resulted in nearly 0% convergence rates for the handful of models selected to explore this possible solution. A study by Tueller, Drotar, and Lubke (2011) initially stood out as a promising resource for solving the label switching issue in this LTA simulation. The authors designed an algorithm in R to detect potential instances of switched labels and either correct them or flag them for exclusion from a simulation due to ambiguous labels. This algorithm requires as input the class assignment matrix produced by *Mplus* (or similar software) when running cross-sectional latent variable mixture models. Unfortunately, the LTA model output does not provide this matrix, so an alternative correction procedure was required.

⁷ It should be noted that fit indices are unaffected by label switching and there is no resulting impact on summarizing index values across multiple replications.

Designing an identification and correction algorithm for LTA class switching could constitute its own independent study, and it is entirely possible that the procedure designed for the current study is overly simplistic and/or conservative. Luckily, most instances of possible class switching were fairly blatant due to the generation of highly defined latent class parameters. Inspired by these patterns of blatant switching, a detection method based on the estimated sets of item response parameters, specifically, was designed and deployed with reasonable confidence. The procedure entailed computing the distances from estimated within-class item response parameters to their known population-generated values, computing similar distances to their counterparts generated for other latent classes, and comparing sets of distances.⁸ For example, the set of five item response probabilities estimated for the first latent class would be compared to the generated sets of item parameters for the first, second, third, and possibly fourth latent class, depending on whether the three- or four-class solutions were being analyzed. These example comparisons are illustrated in Table 4.9 below.

⁸ This procedure is essentially calculating the absolute value of the absolute bias (i.e., $\hat{\theta} - \theta$) for the true within-class item response parameter for Item j , against each estimated class's j th item response parameter. The estimated class for which bias is the most minimal is presumably the intended estimated class, and the labels should be corrected, where applicable.

Table 4.9. Illustration of Class Switching Identification Procedure

Estimated item response probability for Class 1*		Generated population item response parameters			
		Class 1	Class 2	Class 3	Class 4
$\hat{\rho}_{r1 C=1}$	Compared to...	$\rho_{r1 C=1}$	$\rho_{r1 C=2}$	$\rho_{r1 C=3}$	$\rho_{r1 C=4}$
$\hat{\rho}_{r2 C=1}$	Compared to...	$\rho_{r2 C=1}$	$\rho_{r2 C=2}$	$\rho_{r2 C=3}$	$\rho_{r2 C=4}$
$\hat{\rho}_{r3 C=1}$	Compared to...	$\rho_{r3 C=1}$	$\rho_{r3 C=2}$	$\rho_{r3 C=3}$	$\rho_{r3 C=4}$
$\hat{\rho}_{r4 C=1}$	Compared to...	$\rho_{r4 C=1}$	$\rho_{r4 C=2}$	$\rho_{r4 C=3}$	$\rho_{r4 C=4}$
$\hat{\rho}_{r5 C=1}$	Compared to...	$\rho_{r5 C=1}$	$\rho_{r5 C=2}$	$\rho_{r5 C=3}$	$\rho_{r5 C=4}$
The minimum value of the cumulative distances identifies the True Class label for the estimated class →		↓ $\Sigma(\text{distances})$	↓ $\Sigma(\text{distances})$	↓ $\Sigma(\text{distances})$	↓ $\Sigma(\text{distances})$
		\approx cumulative distance from True Class 1	\approx cumulative distance from True Class 2	\approx cumulative distance from True Class 3	\approx cumulative distance from True Class 4

*This process is performed separately for each set of estimated item response probabilities, yielding k independent True Class labels.

The label switching identification procedure was designed to independently compute the True Class identity for each estimated latent class. In rare instances, this led to the algorithm assigning more than one estimated latent class to the same True Class. Simulated replications that were identified with these ambivalent, or conflicting, labeling determinations were flagged for exclusion from the analysis. Rates of identified label switching and conflicting labels are presented across model types in Tables 4.10a to 4.12b below. Once the “correct” labels were identified, the data were conditionally restructured to align like within-class parameters together.

An interesting estimation pattern was discovered among the three-class solutions in which the item parameters generated for the fourth latent class (affectionately dubbed the “ghost class” in this study) emerged as the set of item responses for one of the three estimated latent classes. Table 4.11c illustrates how prevalent ghost class labels were across all model types, among replications with observed class switching. Models under

LMI Pattern A (i.e., the third class splits into two classes) appear to be more impacted than those under LMI Pattern B, particularly those generated with an 80/20 class prevalence split. Twenty-four three-class models generated with Poorly-Defined, High Thresholds class separation conditions were identified as having ghost labels in 100% of their replications with label switching present. Further, 23 of those 24 models also were identified as having 100% label switching rates—that is, every single converged replication produced item estimates with out-of-sequence class labels, and at least one of the three sets of estimated latent class item parameters closely resembled the ghost class’s population parameters.⁹

The assignment and estimation of ghost class parameters makes sense given the arbitrary selection of latent class labels, but it produced difficulties in handling these cases in the relabeling/correctional part of the procedure. In order to calculate and summarize parameter recovery among k -class models, k sets of population-generated parameter values are required for comparison. Therefore, when only three of four generated latent classes are estimated, only three sets of population parameters are needed for bias calculations. One class must remain “un-estimated,” and it is logical in the context of this simulation to make the fourth class un-estimated. All replications with evidence of ghost class labels were also flagged for exclusion from the analysis. Tables

⁹ One thing to consider, from a practitioner’s perspective, is the class enumeration decision that accompanies these models with particularly high rates of conflicting and/or ghost labels. All of the 24 three-class models with 100% rates of label switching are based on generated data for which a four-class solution is uniformly chosen as best-fitting by AIC and ABIC. Indeed, the k -class models with the lowest rates of problematic labeling tend to be the models that are chosen as best-fitting class solutions for the underlying dataset. This may bode well for the empirical researcher trying to avoid discarding results due to class label switching.

A.1 and A.2 in Appendix A provide final counts of replications included in the analytical samples for this study.

Table 4.10a. Rates of Two-Class Model Replications Containing Identified Class Label Switching

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.618	0.188	0.094	0.303	0.770
			500	0.728	0.136	0.024	0.327	0.630
			1000	0.672	0.066	0.016	0.258	0.448
		60/40	200	0.680	0.232	0.088	0.394	0.424
			500	0.680	0.304	0.094	0.453	0.386
			1000	0.640	0.374	0.084	0.416	0.434
		80/20	200	0.388	0.550	0.220	0.186	0.692
			500	0.472	0.608	0.228	0.106	0.474
			1000	0.406	0.386	0.246	0.069	0.250
	Unordered	50/50	200	0.579	0.154	0.070	0.313	0.810
			500	0.644	0.098	0.014	0.270	0.764
			1000	0.626	0.086	0.018	0.214	0.646
		60/40	200	0.646	0.196	0.076	0.422	0.768
			500	0.606	0.184	0.064	0.398	0.916
			1000	0.578	0.256	0.090	0.306	0.966
		80/20	200	0.315	0.544	0.198	0.172	0.718
			500	0.430	0.538	0.200	0.116	0.480
			1000	0.426	0.300	0.220	0.082	0.290
B	Ordered	50/50	200	0.582	0.236	0.062	0.384	0.342
			500	0.576	0.216	0.054	0.464	0.346
			1000	0.606	0.216	0.062	0.426	0.296
		60/40	200	0.584	0.236	0.062	0.411	0.328
			500	0.652	0.164	0.048	0.456	0.326
			1000	0.596	0.178	0.060	0.414	0.300
		80/20	200	0.610	0.176	0.076	0.443	0.330
			500	0.678	0.198	0.064	0.492	0.332
			1000	0.634	0.128	0.050	0.438	0.258
	Unordered	50/50	200	0.546	0.470	0.182	0.369	0.792
			500	0.512	0.340	0.176	0.418	0.796
			1000	0.514	0.186	0.166	0.346	0.748
		60/40	200	0.576	0.394	0.162	0.410	0.840
			500	0.576	0.278	0.132	0.389	0.792
			1000	0.562	0.106	0.148	0.334	0.700
		80/20	200	0.642	0.234	0.076	0.421	0.588
			500	0.626	0.158	0.114	0.372	0.444
			1000	0.580	0.082	0.104	0.322	0.356

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.10b. Rates of Two-Class Model Replications Containing Conflicting Label Corrections

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.068	0.021	0.000	0.007	0.000
			500	0.019	0.000	0.000	0.000	0.000
			1000	0.006	0.000	0.000	0.000	0.000
		60/40	200	0.047	0.034	0.023	0.005	0.000
			500	0.003	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.062	0.000	0.000	0.000	0.000
			500	0.004	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
	Unordered	50/50	200	0.055	0.013	0.000	0.000	0.000
			500	0.012	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.028	0.010	0.000	0.009	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.064	0.000	0.000	0.000	0.000
			500	0.005	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
B	Ordered	50/50	200	0.027	0.000	0.000	0.005	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.003	0.000	0.000	0.000	0.000
		60/40	200	0.024	0.000	0.000	0.005	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.026	0.023	0.000	0.000	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
	Unordered	50/50	200	0.033	0.000	0.000	0.005	0.000
			500	0.004	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.035	0.000	0.000	0.005	0.000
			500	0.003	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.019	0.026	0.000	0.005	0.000
			500	0.003	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.11a. Rates of Three-Class Model Replications Identified as Containing Class Label Switching

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.547	0.591	0.500	0.420	1.000
			500	0.324	0.698	0.422	0.418	1.000
			1000	0.168	0.610	0.414	0.446	1.000
		60/40	200	0.398	0.602	0.562	0.470	0.905
			500	0.222	0.702	0.624	0.512	0.996
			1000	0.147	0.566	0.562	0.542	1.000
		80/20	200	0.869	0.666	0.608	0.700	1.000
			500	0.878	0.735	0.717	0.695	1.000
			1000	0.886	0.803	0.758	0.661	1.000
	Unordered	50/50	200	0.489	0.524	0.399	0.355	1.000
			500	0.249	0.596	0.434	0.345	1.000
			1000	0.092	0.624	0.390	0.314	1.000
		60/40	200	0.360	0.406	0.456	0.404	0.517
			500	0.170	0.480	0.468	0.406	0.744
			1000	0.100	0.484	0.430	0.353	0.819
		80/20	200	0.780	0.623	0.498	0.610	1.000
			500	0.784	0.599	0.502	0.559	1.000
			1000	0.773	0.649	0.503	0.437	1.000
B	Ordered	50/50	200	0.555	0.364	0.158	0.502	1.000
			500	0.354	0.298	0.078	0.561	1.000
			1000	0.340	0.208	0.036	0.590	1.000
		60/40	200	0.459	0.366	0.158	0.510	0.992
			500	0.318	0.376	0.086	0.587	1.000
			1000	0.288	0.286	0.040	0.604	1.000
		80/20	200	0.423	0.342	0.226	0.494	0.764
			500	0.296	0.258	0.174	0.611	0.916
			1000	0.249	0.164	0.134	0.666	0.980
	Unordered	50/50	200	0.568	0.414	0.366	0.443	1.000
			500	0.400	0.422	0.346	0.481	1.000
			1000	0.243	0.362	0.232	0.512	1.000
		60/40	200	0.522	0.440	0.376	0.429	0.998
			500	0.271	0.402	0.332	0.481	1.000
			1000	0.210	0.338	0.326	0.464	1.000
		80/20	200	0.422	0.394	0.408	0.400	0.785
			500	0.226	0.212	0.332	0.426	0.942
			1000	0.163	0.110	0.362	0.433	0.984

Note. Bolded cells indicate models that yielded a *best-fitting* three-class solution (per AIC). WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds, PD/MT = poorly-defined, moderate thresholds, PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.11b. Rates of Three-Class Model Replications Containing Conflicting Label Corrections

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.015	0.000	0.000	0.019	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.030	0.000	0.000	0.004	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.000	0.000	0.000	0.014	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
	Unordered	50/50	200	0.016	0.000	0.000	0.017	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.039	0.000	0.000	0.010	0.024
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.000	0.000	0.000	0.039	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
B	Ordered	50/50	200	0.004	0.000	0.000	0.016	0.000
			500	0.006	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.017	0.000	0.000	0.008	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.029	0.000	0.000	0.008	0.029
			500	0.000	0.000	0.000	0.000	0.002
			1000	0.000	0.000	0.000	0.000	0.000
	Unordered	50/50	200	0.011	0.000	0.000	0.027	0.000
			500	0.005	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		60/40	200	0.031	0.000	0.000	0.028	0.008
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
		80/20	200	0.057	0.000	0.000	0.010	0.033
			500	0.000	0.000	0.000	0.000	0.002
			1000	0.000	0.000	0.000	0.000	0.000

Note. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.11c. Rates of Three-Class Model Replications Containing “Ghost Class” Labels

Class Separation (via item response parameter patterns)								
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.571	0.106	0.032	0.119	1.000
			500	0.652	0.037	0.005	0.019	1.000
			1000	0.590	0.003	0.000	0.000	1.000
		60/40	200	0.162	0.000	0.000	0.021	0.985
			500	0.027	0.000	0.000	0.000	1.000
			1000	0.000	0.000	0.000	0.000	1.000
		80/20	200	0.935	0.939	0.893	0.837	1.000
			500	0.963	0.981	0.912	0.821	1.000
			1000	0.986	0.990	0.978	0.838	1.000
	Unordered	50/50	200	0.496	0.050	0.010	0.124	1.000
			500	0.516	0.000	0.000	0.000	1.000
			1000	0.413	0.000	0.000	0.000	1.000
		60/40	200	0.122	0.000	0.000	0.010	0.820
			500	0.000	0.000	0.000	0.000	0.877
			1000	0.000	0.000	0.000	0.000	0.933
		80/20	200	0.920	0.876	0.921	0.777	1.000
			500	0.910	0.933	0.988	0.691	1.000
			1000	0.922	0.966	0.992	0.647	1.000
B	Ordered	50/50	200	0.457	0.049	0.038	0.044	1.000
			500	0.369	0.007	0.000	0.000	1.000
			1000	0.180	0.000	0.000	0.000	1.000
		60/40	200	0.293	0.016	0.000	0.027	1.000
			500	0.191	0.000	0.000	0.000	1.000
			1000	0.043	0.000	0.000	0.000	1.000
		80/20	200	0.110	0.000	0.000	0.004	0.855
			500	0.014	0.000	0.000	0.000	0.958
			1000	0.000	0.000	0.000	0.000	0.984
	Unordered	50/50	200	0.518	0.130	0.049	0.090	1.000
			500	0.551	0.024	0.000	0.004	1.000
			1000	0.454	0.000	0.000	0.000	1.000
		60/40	200	0.352	0.050	0.005	0.079	0.996
			500	0.328	0.000	0.000	0.000	1.000
			1000	0.175	0.000	0.000	0.000	1.000
		80/20	200	0.129	0.000	0.000	0.025	0.862
			500	0.045	0.000	0.000	0.000	0.970
			1000	0.000	0.000	0.000	0.000	0.996

Note. The denominator is the number of replications with identified label switching, not the total number of converged replications. Bolded cells ($N = 23$) indicate models with 100% of their replications containing evidence of label switching. Since replications with either conflicting or “ghost class” labels are excluded from aggregate measures of bias, these 23 models will be completely excluded from the three-class bias calculations. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds; PD/MT = poorly-defined, moderate thresholds; PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.12a. Rates of Four-Class Model Replications Containing Identified Class Label Switching

				Class Separation (via item response parameter patterns)				
LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.687	0.446	0.294	0.585	0.050
			500	0.663	0.367	0.203	0.344	0.005
			1000	0.711	0.508	0.240	0.336	0.000
		60/40	200	0.864	0.463	0.264	0.822	0.066
			500	0.720	0.316	0.176	0.741	0.011
			1000	0.619	0.279	0.177	0.622	0.007
		80/20	200	0.561	0.399	0.278	0.259	0.058
			500	0.605	0.483	0.185	0.279	0.005
			1000	0.624	0.582	0.279	0.240	0.000
	Unordered	50/50	200	0.722	0.433	0.307	0.622	0.064
			500	0.690	0.372	0.245	0.464	0.008
			1000	0.702	0.419	0.174	0.319	0.000
		60/40	200	0.920	0.500	0.289	0.838	0.113
			500	0.860	0.358	0.112	0.849	0.005
			1000	0.713	0.281	0.127	0.767	0.000
		80/20	200	0.589	0.366	0.272	0.290	0.082
			500	0.530	0.360	0.196	0.241	0.012
			1000	0.574	0.476	0.192	0.249	0.002
B	Ordered	50/50	200	0.756	0.755	0.861	0.543	0.035
			500	0.726	0.795	0.790	0.297	0.004
			1000	0.770	0.787	0.803	0.245	0.000
		60/40	200	0.745	0.723	0.877	0.678	0.027
			500	0.690	0.783	0.802	0.461	0.004
			1000	0.699	0.703	0.845	0.252	0.000
		80/20	200	0.885	0.603	0.765	0.819	0.039
			500	0.768	0.410	0.727	0.773	0.006
			1000	0.582	0.325	0.739	0.636	0.000
	Unordered	50/50	200	0.723	0.675	0.790	0.554	0.037
			500	0.715	0.563	0.490	0.333	0.000
			1000	0.754	0.371	0.302	0.288	0.000
		60/40	200	0.710	0.677	0.775	0.668	0.033
			500	0.697	0.544	0.457	0.476	0.000
			1000	0.695	0.310	0.330	0.322	0.000
		80/20	200	0.837	0.640	0.654	0.803	0.050
			500	0.796	0.427	0.489	0.792	0.002
			1000	0.632	0.295	0.306	0.693	0.000

Note. Bolded cells indicate models that yielded a *best-fitting* four-class solution (per AIC). WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds, PD/MT = poorly-defined, moderate thresholds, PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table 4.12b. Rates of Four-Class Model Replications Containing Conflicting Label Corrections

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	0.308	0.000	0.000	0.713	0.000
			500	0.022	0.000	0.000	0.341	0.000
			1000	0.000	0.000	0.000	0.031	--
		60/40	200	0.709	0.066	0.026	0.908	0.000
			500	0.558	0.000	0.000	0.879	0.000
			1000	0.329	0.000	0.000	0.705	0.000
		80/20	200	0.032	0.000	0.000	0.103	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	--
	Unordered	50/50	200	0.478	0.000	0.000	0.800	0.000
			500	0.107	0.000	0.000	0.581	0.000
			1000	0.003	0.000	0.000	0.187	--
		60/40	200	0.825	0.392	0.107	0.927	0.658
			500	0.840	0.029	0.000	0.950	0.500
			1000	0.742	0.000	0.000	0.895	--
		80/20	200	0.061	0.000	0.000	0.149	0.000
			500	0.000	0.000	0.000	0.000	0.000
			1000	0.000	0.000	0.000	0.000	0.000
B	Ordered	50/50	200	0.293	0.000	0.000	0.791	0.000
			500	0.018	0.000	0.000	0.464	0.000
			1000	0.000	0.000	0.000	0.105	--
		60/40	200	0.440	0.000	0.000	0.851	0.000
			500	0.089	0.000	0.000	0.661	0.000
			1000	0.003	0.000	0.000	0.300	--
		80/20	200	0.756	0.076	0.000	0.914	0.111
			500	0.642	0.000	0.000	0.924	0.000
			1000	0.370	0.000	0.000	0.896	--
	Unordered	50/50	200	0.301	0.000	0.000	0.775	0.056
			500	0.017	0.000	0.000	0.360	--
			1000	0.000	0.000	0.000	0.092	--
		60/40	200	0.450	0.000	0.000	0.842	0.000
			500	0.091	0.000	0.000	0.665	--
			1000	0.003	0.000	0.000	0.253	--
		80/20	200	0.793	0.087	0.004	0.907	0.167
			500	0.641	0.000	0.000	0.919	0.000
			1000	0.393	0.000	0.000	0.842	--

Note. "--" indicates that the model did not have any replications with evidence of label switching. WD/LT = well-defined, low thresholds; WD/MT = well-defined, moderate thresholds; WD/HT = well-defined, high thresholds, PD/MT = poorly-defined, moderate thresholds, PD/HT = poorly-defined, high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

PARAMETER AND STANDARD ERROR RECOVERY RESULTS

Model estimates from all three- and four-class solutions were assessed for parameter and standard error recovery. All LTA parameter estimates on a logit scale were transformed to probabilities prior to aggregating for analysis (i.e., all class-specific item response parameters), thus allowing for slight gains in interpretability. It also allowed for the calculation of relative parameter bias for parameters whose population value was generated at zero.

Because there is not a linear relationship between item response probabilities (or logits) and class agreement, interpreting the impact of positive or negative bias in these parameters requires the additional consideration of the population parameter's generated value. For instance, item response probabilities of 0.05 and 0.95 are associated with equally high levels of class agreement, but positive bias (both absolute and relative bias) would have a markedly different interpretation for each parameter. Positive bias for a population parameter generated at 0.95 would indicate an overestimation of within-class agreement. However, positive bias for the 0.05 parameter could indicate either an underestimation of within-class agreement (estimating a value closer to 0.50), or a complete reversal in the direction of response agreement (pushing the value over 0.50 and closer to 1.00).

The calculation of *relative* parameter bias for logit-scaled item response parameters actually yields a directly interpretable relationship with class agreement: positive values of relative bias for logit parameters can always be interpreted as overestimates of within-class agreement, while negative values are underestimates. As

noted above, however, relative bias cannot be calculated for parameters with a true value of zero. A few logit thresholds were set to zero in the population for both Poorly-Defined class separation conditions, corresponding to an item response probability of 0.50. For the purpose of discussing bias among the entire set of item response parameters in this simulation, it was ultimately decided that a probability transformation would be more useful.¹⁰

Relative parameter bias was calculated for all Time 1 item response probability parameters, as discussed above. Absolute bias (i.e., $\hat{\theta} - \theta$) was calculated for both class prevalence parameters and transition probability parameters, as many of the associated population values were generated to be zero. Reference class estimates for prevalence and transition parameters were extrapolated from the set of model-estimated values for each replication and aggregated in the same manner as other model estimates. All model-specific parameter recovery outcomes are available to the reader in Appendix A.

Standard error estimates for the class-specific item response logit parameters were *not* transformed to probabilities, as there is no interpretation issue due to the sign of the estimate and no estimates of the empirical standard error (i.e., the denominator in the RSEB calculation) equaled zero. Standard errors for the extrapolated reference class estimates were not possible to calculate, so relative standard error bias is not addressed

¹⁰ Note that values of relative parameter bias for proportion-scaled parameters are bound at -1.00 for negative bias and $+\infty$ for positive bias. Positive values of relative bias may then be much larger in magnitude than the value of negative relative bias that corresponds to the same magnitude of absolute bias.

for the reference class parameters. All model-specific standard error recovery outcomes are available in Appendix B.

Item Response Probability Parameters

The detailed patterns of substantial item response parameter bias as they relate to study conditions are first presented descriptively, followed by a brief interpretation of the relevant ANOVAs, the latter confirming the statistical and practical significance of the relationships of interest.

Three-Class Solutions

While relative bias was calculated for *all* within-class item response parameters, it was hypothesized that item parameters for the third and fourth (if estimated) latent classes would be most impacted by the forced structural invariance in all models. Figure 4.1 below provides rates of substantial relative bias present across all within-class item response parameters. Interestingly, within three-class solutions, the first two items in the first latent class displayed much higher rates of substantial relative bias than other items.¹¹

¹¹ As explained in Chapter 3, substantial relative bias in this simulation is defined by magnitudes of relative bias greater than or equal to 0.10.

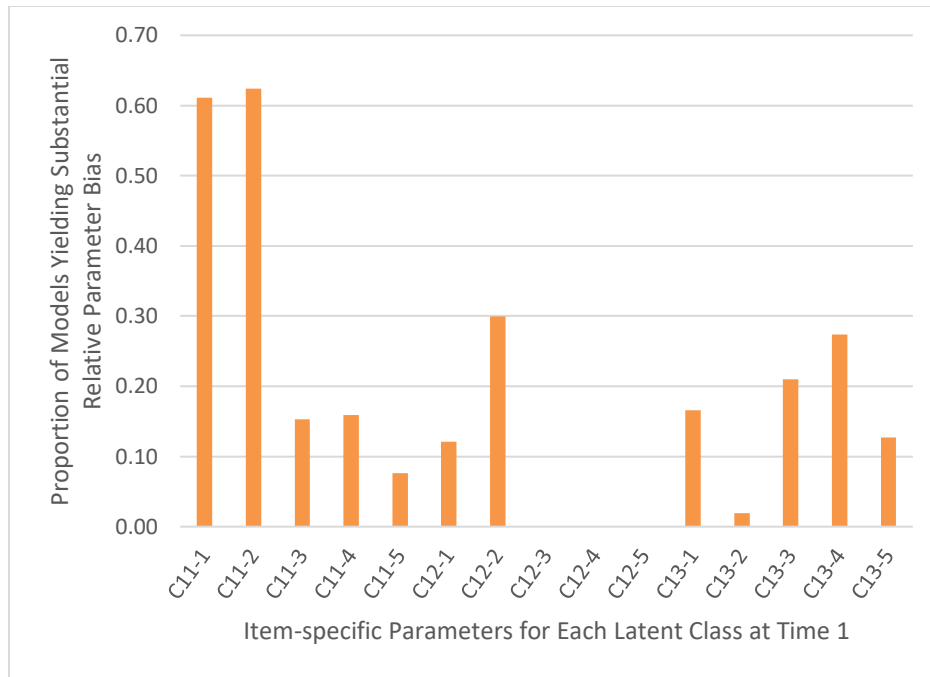


Figure 4.1. Rates of substantial relative bias for item response parameters across all three-class models ($N = 157$)

Tables A.3a to A.7b in Appendix A provide a more granular view of the relative bias in these item parameters. The first two items for Class 1 show uniformly positive bias across all models under the three Well-Defined class separation conditions (Low, Moderate, and High Thresholds). The same items show no substantial bias in the Poorly-Defined class separation conditions. It should be noted that in the latter conditions, those two items are designed with population-generated values reflecting either the lowest class agreement ($\rho = 0.50$) or high rates of item endorsement ($\rho > 0.90$). Therefore, any positive bias would indicate an overestimation of within-class agreement. However, since the substantial positive bias in these two items is evident only when the population-generated proportion is less than 0.50, these models are likely *underestimating* within-

class agreement for these Class 1 items. Indeed, bias is highest for these items when they are generated to have the highest levels of within-class agreement ($\rho = 0.05$), as shown in Tables A.5a and A.5b, suggesting that the forced invariance of these estimating models is not allowing for the estimation of particularly high within-class agreement in the first latent class.

A similar yet less prevalent underestimation of within-class agreement is occurring for the third latent class, which makes sense given the underlying configural non-invariance in the third class across the two time points. There are patterns of substantial underestimation of class agreement for three of these items, specifically under conditions of LMI Pattern A (third class splits into two classes), 50/50 prevalence split (i.e., the largest split), and Well-Defined classes with Low and Moderate Threshold values. LMI Pattern B (third and fourth classes merge into one) combined with the Well-Defined class conditions appear to protect against bias in the item estimates for the third class. In the Poorly-Defined class separation conditions, item parameters in Class 3 exhibit variability in both under- and overestimating within-class agreement (see Tables A.6a through A.7b).

The smallest amount of bias among the three-class solutions was found in the second latent class. Three of the five item parameters for this class exhibited no substantial relative bias at all, though the first two item parameters were frequently underestimated—in their case, meaning that within-class agreement was overestimated, as they were both generated with low class agreement across all models.

Four-Class Solutions

In models that estimated four latent classes at each time point, substantial relative bias for the within-class item response parameters was most prevalent in the third and fourth classes, as expected (see Figure 4.2 below). Tables A.9a to A.12b in Appendix A provide model-specific bias details. Between these two classes, only Class 4 items showed substantial bias in the Well-Defined class separation conditions, and that bias was relatively infrequent—only appearing in small sample size conditions, more so in the 80/20 prevalence split for LMI Pattern B. As was seen in the three-class solutions, the direction of the bias indicated an underestimation of latent class agreement for these items. Substantial bias in Class 3 items did not materialize until the models were generated under Poorly-Defined class separation conditions (see Tables A.11a through A.12b in Appendix A). Unlike the patterns of bias seen for the fourth latent class, the patterns for Class 3 suggest a general overestimation of within-class agreement for the affected items.

The first and second latent classes exhibited moderate rates of substantial relative bias in their item parameters. At least one item in both classes showed some overestimating of class agreement, particularly in the lowest sample size conditions and when the item thresholds were generated with “low” values. Higher threshold values appear to be protective against this type of bias in Classes 1 and 2.

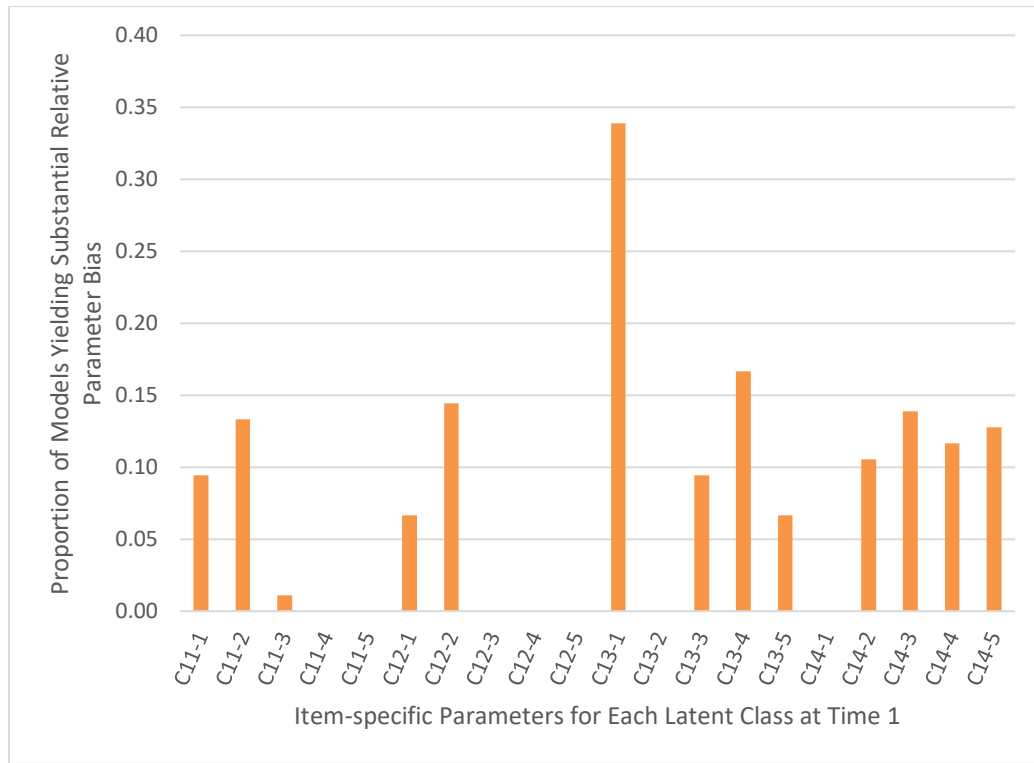


Figure 4.2 Rates of substantial relative bias for item response parameters across all four-class models ($N = 180$)

ANOVA Results for Item Response Parameter Bias

In order to determine which, if any, model conditions discussed above are significantly and/or practically related to bias in item response parameters, results from ANOVAs with main effects and two-way interactions of study conditions are presented below. Only results for analyses of the first and third latent classes' item parameters are shown, as those items displayed the highest rates of substantial relative parameter bias under the simulated conditions. Table 4.13 shows the general patterns of significant impacts on Class 1's item parameters, and Table 4.14 provides the same for Class 3.

Table 4.13. ANOVA of the Relative Parameter Bias of the Time 1 Class 1 Item Response Probability Parameters

Time 1 Class 1 Item Response Probability Parameters					
	Item 1	Item 2	Item 3	Item 4	Item 5
<i>Number of Models</i>	337	337	337	337	337
CE	***	***	***	***	***
TP					
LMI					
N					
CS	***	***	***	***	***
CPS					
CE*LMI					
CE*TP					
CE*N					
CE*CS	***	***	***	***	***
CE*CPS					***
LMI*N					
LMI*CS					
LMI*CPS					
LMI*TP					
N*CS					
N*CPS					
N*TP					
CS*CS					
CS*TP					
TP*CPS					
	: $p < 0.05$ and $\eta^2 \geq 0.06$ (both statistically and practically significant)				
	: $p < 0.05$ and $\eta^2 < 0.06$ (statistically significant only)				
	: $p \geq 0.05$ and $\eta^2 \geq 0.06$ (practically significant only)				

Note. CE = class enumeration (3-class, 4-class solutions); TP = transition pattern (ordered, unordered); LMI = longitudinal measurement invariance pattern (3→4, 4→3); N = total sample size (200, 500, 1000); CS = class separation (well-defined/low thresholds, well-defined/moderate thresholds, well-defined/high thresholds, poorly-defined/moderate thresholds, poorly-defined/high thresholds); CPS = class prevalence split (50/50, 60/40, 80/20). “***” indicates that the main effect or interaction is associated with one of the top three highest partial eta-squared values.

Each of the Class 1 item parameters’ estimation was impacted by class enumeration (i.e., whether a three- or a four-class solution was modeled), class separation, and class prevalence splits. Further, the impact of both class separation and class prevalence splits differed according to the number of classes estimated, and the interaction of the two manipulated conditions showed both statistical and practical significance. Whether the data were generated with ordered or unordered transition matrices did not have a practical impact on item parameter estimation. These results align

well with the relationships discussed in detail in the preceding sections as well as those shown in Appendix A.

For item response parameter estimates in Class 3, both the main effect of class enumeration and its interaction with class separation significantly impact all item parameter estimates. Several items are also impacted by class separation and its interactions with LMI Pattern, sample size, and class prevalence splits. The design of the underlying transition matrix had no practical impact on these parameters, as we saw for Class 1 item parameters above.

Table 4.14. ANOVA of the Relative Parameter Bias of the Time 1 Class 3 Item Response Probability Parameters

Time 1 Class 3 Item Response Probability Parameters					
	Item 1	Item 2	Item 3	Item 4	Item 5
<i>Number of Models</i>	337	337	337	337	337
CE	***		***	***	***
TP					
LMI					
N					
CS		***		***	***
CPS					
CE*LMI					
CE*TP					
CE*N					
CE*CS	***	***	***	***	***
CE*CPS					
LMI*N					
LMI*CS	***				
LMI*CPS					
LMI*TP					
N*CS		***	***		
N*CPS					
N*TP					
CS *CPS					
CS *TP					
TP*CPS					
	: $p < 0.05$ and $\eta^2 \geq 0.06$ (both statistically and practically significant)				
	: $p < 0.05$ and $\eta^2 < 0.06$ (statistically significant only)				
	: $p \geq 0.05$ and $\eta^2 \geq 0.06$ (practically significant only)				

Note. CE = class enumeration (3-class, 4-class solutions); TP = transition pattern (ordered, unordered); LMI = longitudinal measurement invariance pattern (3→4, 4→3); N = total sample size (200, 500, 1000); CS = class separation (well-defined/low thresholds, well-defined/moderate thresholds, well-defined/high thresholds, poorly-defined/moderate thresholds, poorly-defined/high thresholds); CPS = class prevalence split (50/50, 60/40, 80/20). “***” indicates that the main effect or interaction is associated with one of the top three highest partial eta-squared values.

Class Prevalence Parameters

Absolute parameter bias for class prevalence parameter estimates is discussed next, for both three- and four-class solutions. Tables A.13a to A.14b in Appendix A provide all model-specific values of absolute parameter bias for this set of prevalence parameters. Since there is no cited threshold for “substantial” absolute bias, this section will simply describe the overall trends in direction and magnitude of parameter bias seen

in the tables in Appendix A. Then, the ANOVA results will be presented to attribute to these patterns a measure of statistical and practical significance.

Three-Class Solutions

Among the three-class solutions, data generated under LMI Pattern B appear to yield higher levels of absolute bias in class prevalence parameter estimates. Specifically, when a three-class model is forced on four classes that merge into one, membership for the first latent class tends to be overestimated, particularly as the generated class prevalence split gets larger. The opposite is apparent for the third latent class, which tends to have its membership underestimated across LMI Pattern B models.

Four-Class Solutions

When four classes are estimated by the models, values of absolute parameter bias are relatively low across both generated LMI pattern groups. For Class 3, which is hypothesized to be the most impacted by study conditions, class membership is generally underestimated. This relationship is slightly magnified under the Poorly-Defined, Moderate Thresholds class separation condition. When a fourth class is generated at Time 1 (i.e., under LMI Pattern B), the four-class models tend to slightly overestimate its class prevalence parameter. This relationship is also magnified under the Low and Moderate Threshold conditions.

ANOVA Results for Class Prevalence Parameter Bias

Statistical and practical significance for the relationships described above are presented in Table 4.15. Class prevalence estimates were estimated differentially based on several study factors. For example, the significant interaction between class enumeration and LMI pattern is clear when we examine Class 1, which is consistently underestimated in all four-class solutions and three-class solutions with LMI Pattern A. However, the class's membership is suddenly overestimated when three-class models are generated under LMI Pattern B. Further, the subtle interactions described above among LMI Pattern, class prevalence split, and class separation emerged as both statistically and practically significant.

Table 4.15. ANOVA of the Absolute Parameter Bias of the Time 1 Class Prevalence Parameters

Time 1 Class Prevalence Parameters				
	Class 1	Class 2	Class 3	Class 4
<i>Number of Models</i>	337	337	337	180
CE	***		***	
TP				
LMI	***	***	***	
N				***
CS		***		***
CPS				
CE*LMI	***		***	
CE*TP				
CE*N				
CE*CS				
CE*CPS				
LMI*N				
LMI*CS		***		
LMI*CPS				
LMI*TP				
N*CS				***
N*CPS				
N*TP				
CS*CPS				
CS*TP				
TP*CPS				
	: $p < 0.05$ and $\eta^2 \geq 0.06$ (both statistically and practically significant)			
	: $p < 0.05$ and $\eta^2 < 0.06$ (statistically significant only)			
	: $p \geq 0.05$ and $\eta^2 \geq 0.06$ (practically significant only)			

Note. CE = class enumeration (3-class, 4-class solutions); TP = transition pattern (ordered, unordered); LMI = longitudinal measurement invariance pattern (3→4, 4→3); N = total sample size (200, 500, 1000); CS = class separation (well-defined/low thresholds, well-defined/moderate thresholds, well-defined/high thresholds, poorly-defined/moderate thresholds, poorly-defined/high thresholds); CPS = class prevalence split (50/50, 60/40, 80/20). ‘***’ indicates that the main effect or interaction is associated with one of the top three highest partial eta-squared values.

Transition Probability Parameters

Absolute bias was also used to assess the recovery of the transition parameters, as several transition probabilities generated for the underlying data were set to zero, thus rendering relative bias incalculable. Model-specific breakdowns of absolute bias values for this set of parameters are provided in Appendix A, Tables A.15a through A.16d.

Three-Class Solutions

The generated LMI Pattern appears to play a large role in transition parameter bias when a three-class model is forced on the data. Under Pattern A (the third class splits into two), three distinct relationships emerge: 1) The likelihood of members of Class 2 remaining in their latent class is underestimated under Well-Defined, Low Threshold class separation conditions and both ordered and unordered transition matrix designs; 2) the estimation of Class 3 members transitioning to Class 1 is overestimated in the 50/50 and 80/20 prevalence splits, for both ordered and unordered transition matrix designs; and 3) the estimation of Class 3 members remaining in Class 3 is symmetrically underestimated in all situations mentioned in (2). That is, a substantial proportion of Class 3 members that were generated to remain in Class 3 over time were estimated to transition to Class 1 at Time 2.

For models generated under LMI Pattern B (Classes 3 and 4 merging over time), it appears that a substantial proportion of Class 1 members that were generated to remain in that class were estimated to transition to Class 3, instead. This relationship was fairly consistent across all models under LMI Pattern B, but was amplified as the class prevalence split became larger. A slightly less dramatic “switching” pattern emerged for Class 3, such that Class 3 members that were generated to stay in their class were estimated as transitioning to Class 2, mainly in the Well-Defined, Low Thresholds class separation condition.

Four-Class Solutions

For four-class solutions, the Well-Defined, Low Thresholds class separation condition also appeared to impact the members of Classes 1 and 2 that were meant to remain in their classes, and they are seen transitioning to the other classes, instead. This pattern also emerges for the Poorly-Defined, Moderate Thresholds group, but only under LMI Pattern B.

An odd pattern emerges for Class 3 under LMI Pattern A, depending on the class prevalence split condition. The 80/20 prevalence split sees members that were supposed to remain in Class 3 instead transitioning to Class 4, but the 60/40 prevalence split sees a proportion of the Class 3-to-4 transitioners instead remaining in Class 3. The 50/50 split is associated with negligible bias in the Class 3 transitions. Under LMI Pattern B, Class 3 members that were meant to remain in their class were more likely to transition to both Classes 2 and 4, particularly when the class separation was designed under Well-Defined, Low Thresholds; Poorly-Defined, Moderate Thresholds; and Poorly-Defined, High Thresholds conditions.

For LMI Pattern A, which generates a fourth latent class at Time 1 and therefore has calculable bias values for Class 4 transitions, sees all of its members that were meant to merge into Class 3 instead remaining in the estimated Class 4 or transitioning to Class 1 or 2. Similar to other instances of bias in transition parameters, these patterns are more evident among models generated under Well-Defined, Low Thresholds and both Poorly-Defined class separation conditions.

ANOVA Results for Class Transition Parameter Bias

The relationships among transition parameter bias and study conditions discussed in the previous section are assessed for statistical and practical significance in Table 4.16 below. The main effect of class separation was significantly related to bias in all transition parameter estimates. Further, the relationships between class separation and sample size, LMI Pattern, and class prevalence split provided additional significant influence on transition parameter bias. LMI Pattern and its interactions with other study factors had an expected significant impact on Class 4, in particular.

Table 4.16. ANOVA of the Absolute Parameter Bias of the Transition Matrix Probability Parameters

	Transition Matrix Probability Parameters															
	C21 on C11	C22 on C11	C23 on C11	C24 on C11	C21 on C12	C22 on C12	C23 on C12	C24 on C12	C21 on C13	C22 on C13	C23 on C13	C24 on C13	C21 on C14	C22 on C14	C23 on C14	C24 on C14
<i>Number of Models</i>	337	337	337	180	337	337	337	180	337	337	337	180	180	180	180	180
CE	****		****		****				****							
TP																
LMI	****		****		****				****	****	****	****	****	****	****	****
N				****				****								
CS		****		****	****	****		****		****			****	****	****	****
CPS											****	****				****
CE*LMI	****		****						****							
CE*TP																
CE*N																
CE*CS		****					****									
CE*CPS																
LMI*N																
LMI*CS		****				****	****			****	****		****	****	****	
LMI*CPS											****	****				
LMI*TP																
N*CS				****		****	****	****								
N*CPS																
N*TP																
CS*CPS																
CS*TP																
TP*CPS																
	: $p < 0.05$ and $\eta^2 \geq 0.06$ (both statistically and practically significant)															
	: $p < 0.05$ and $\eta^2 < 0.06$ (statistically significant only)															
	: $p \geq 0.05$ and $\eta^2 \geq 0.06$ (practically significant only)															

Note. CE = class enumeration (3-class, 4-class solutions); TP = transition pattern (ordered, unordered); LMI = longitudinal measurement invariance pattern (3→4, 4→3); N = total sample size (200, 500, 1000); CS = class separation (well-defined/low thresholds, well-defined/moderate thresholds, well-defined/high thresholds, poorly-defined/moderate thresholds, poorly-defined/high thresholds); CPS = class prevalence split (50/50, 60/40, 80/20). '****' indicates that the main effect or interaction is associated with one of the top three highest partial eta-squared values.

Relative Standard Error Bias

Relative standard error bias (RSEB) was calculated for all parameters discussed in the previous section to illustrate the extent to which a model overestimates or underestimates the sampling variability of a parameter. The exception being for the class prevalence and transition parameters for the reference class, as extrapolating standard error estimates for these parameters was not possible. This problem was also reflected as a direct result of class label switching: For replications that showed evidence of an estimated class being assigned the generated reference class's label, it was feasible to extrapolate the parameter estimates for that class from other class parameters, but again, the standard errors could not be computed. Therefore, the number of replications with valid standard error estimates within each set of model conditions varied greatly. The tables of RSEB presented in Appendix B provide the number of converged replications for each model type, but it should be noted that the number of valid standard error estimates within those sets of converged replications may be much lower, and will vary across parameter estimates within the model. Because of the volatility in the ability to produce valid standard errors, patterns in RSEB will be discussed descriptively only.

Standard Errors for Item Response Parameters

Standard error recovery across the manipulated models for item response parameters was generally poor for both three- and four-class solutions. The only protective factor against substantial item RSEB seems to be larger sample sizes (i.e., $N =$

1,000 in this simulation), but there are several combinations of conditions that overpower this protective effect and produce substantial negative and positive RSEB.

Three-Class Solutions

When three-class models are fit to the data, many different patterns in RSEB emerge. Under the conditions of LMI Pattern A and Well-Defined, Low Threshold class separation (see Table B.1a), standard errors for the first two items in Class 1 are consistently overestimated, particularly within the $N = 200$ condition. These were the two items for which within-class agreement was consistently underestimated in the three-class solutions. The remaining items for Class 1 tend to have substantially underestimated standard errors within the lowest sample size condition, except for those in the 80/20 class prevalence split. The standard errors for item parameters in Class 2 are more likely to be underestimated when $N = 200$ and overestimated as the sample size increases. Substantial underestimation of standard errors is the most common form of RSEB seen among the items in Class 3.

Table B.1b provides levels of RSEB for the same set of conditions above, but for LMI Pattern B. There are fewer noticeable patterns for this combination. While underestimation of standard errors at low sample sizes is evident for the items in Class 2 generated with an unordered transition matrix, the remaining combinations of conditions yield a fairly even mix of substantial positive and negative RSEB. Tables B.2a and B.2b provide RSEB calculations for the Well-Defined, Moderate Thresholds class separation condition. Again, we see substantial RSEB within the first two items of Class 1, however

they are now underestimated instead of the overestimation that was present in the Well-Defined, Low Thresholds models. RSEB among the items for Class 3 are substantially underestimated, holding all other study conditions constant. The Well-Defined, High Thresholds condition produces similar patterns to the Well-Defined, Moderate Thresholds condition, but with slightly more prevalent substantial negative RSEB.

An interesting pattern emerged in the Poorly-Defined, Moderate Thresholds condition, such that items designed with higher within-class agreement (i.e., $\rho = 0.95, 0.05, 0.02$) tend to show substantially underestimated standard errors, while items designed with lower within-class agreement (i.e., $\rho = 0.50, 0.40, 0.30$) tend to show overestimated standard errors. This pattern was evident among models generated with both LMI Patterns A and B. The three-class models with Poorly-Defined, High Threshold class separation did not produce an adequate number of converged replications with valid standard errors to warrant a discussion, though, nor did they seem to have a nascent pattern based on within-class agreement like the one seen for Poorly-Defined, Moderate Threshold conditions (see Tables B.5a and B.5b).

Four-Class Solutions

The four-class models generated under Well-Defined, Low Thresholds showed a very strong relationship between lower sample sizes and substantial negative RSEB. Otherwise, the standard errors were generally overestimated (see Tables B.6a and B.6b). For Well-Defined, Moderate Threshold conditions, substantial bias in either direction was rampant, particularly at lower sample sizes. For the unordered transition conditions, the

impact is mainly on the standard errors associated with items in Class 3 and Class 4 (if estimated). Models with Well-Defined High Threshold separation show consistently underestimated standard errors for the $N = 200$ condition. The impact of class prevalence split appears to be higher for the item standard errors in Class 4, with the 50/50 and 60/40 conditions producing consistently negative RSEB.

The Poorly-Defined separation conditions both produce very high rates of substantial RSEB in either direction. Almost all model combinations yield substantial RSEB (see Tables B.9a through B.10b). Some slight patterns emerge within estimated Classes 3 and 4, such that the standard errors for four of the five items in Class 4 are substantially underestimated and the fifth is overestimated. That pattern is reversed in Class 3. It is not surprising to see that these models have trouble producing consistent item estimates, given the forced constraints on the underlying non-invariant data.

Standard Errors for Class Prevalence Parameters

Within three-class models generated under LMI Pattern A, all instances of substantial RSEB are positive (see Table B.11a). The lone exception is for one of the Poorly-Defined, High Threshold conditions, but it is based on only two replications. Most of the substantial bias is seen in the Well-Defined, Low Threshold and Poorly-Defined, Moderate Threshold conditions, and the ordered transition pattern is more likely to produce RSEB in the Well-Defined, High Threshold and Poorly-Defined, Moderate Threshold conditions. Three-class models based on LMI Pattern B also produce predominantly positive RSEB, which increases at the lower sample size conditions (see

Table B.11b). The only underestimating of standard errors for the prevalence parameters is seen in the Well-Defined, High Threshold and Poorly-Defined, Moderate Threshold conditions for Class 1, in both the unordered and ordered transition conditions. The same class separation conditions overestimate the class prevalence standard errors for Class 2 (in the ordered transition condition, only).

Four-class models fit to the simulated data also show consistently high rates of positive RSEB, including some extreme outliers when the data were generated under the conditions of LMI Pattern A, unordered transition matrix, 60/40 prevalence split, and Well-Defined, High Thresholds (see Table B.12a). The high-threshold conditions under LMI Pattern B also produce the highest levels of positive RSEB (see Table B.12b), but the values are nowhere near the magnitude of those seen in the LMI Pattern A table.

Standard Errors for Transition Parameters

The transition parameters for three-class models saw consistently overestimated standard errors under LMI Pattern A combined with the lowest threshold separation conditions, with $N = 1,000$ being somewhat protective in the Well-Defined, Low Thresholds condition (see Table B.13a). The highest level of standard error overestimation is linked to the parameter that estimates the transition from Class 3 to Class 2 when an ordered transition matrix is generated. Conversely, Class 3 to Class 1 transition standard errors tend to be underestimated for the Well-Defined, Moderate and High Thresholds conditions. The Poorly-Defined, Moderate Threshold condition substantially overestimated almost all standard errors for the transition parameters.

Three-class models based on data generated with LMI Pattern B also show consistently inflated transition parameter standard errors within the lowest threshold separation conditions (see Table B.13b). Transition parameters for Classes 2 and 3 have particularly high levels of RSEB, although outliers are seen in models with extremely small numbers of converged replications. The standard errors associated with the probability of remaining in Class 1 are substantially underestimated under several conditions.

All four-class models saw substantial positive RSEB across the board, particularly under low sample size conditions (see Tables B.14a through B.14d). The highest levels of bias for LMI Pattern A were seen in Classes 3 and 4, as expected. When the data were generated under LMI Pattern B, the High Threshold class separation conditions both produced the most extreme levels of positive RSEB. The $N = 1,000$ sample size condition tended to reduce the magnitude of RSEB, but the values of bias remained above the “substantial” threshold in most cases.

Chapter 5: Discussion

LTA is gaining traction as a flexible person-centered approach to modeling change among homogenous latent classes over time, particularly within the social, behavioral, and health sciences. As for any longitudinal modeling framework, shifts in measurement properties across time can introduce ambiguities to the interpretation of the growth parameter estimated. Violations to LMI can manifest in several different ways within the LTA framework, yet there are very few existing studies that tackle the impact of non-invariant, time-specific measurement conditions in LTAs or other growth mixture models.

In this study, we have explored one of the more straightforward types of LTA non-invariance seen in the empirical literature: configural non-invariance, as demonstrated by unequal numbers of latent classes estimated at each measurement occasion. While it would be ideal to see a rise in the popularity of the class enumeration technique that draws upon separate, time-specific LCA enumeration decisions—thus allowing for the acknowledgement of configural non-invariance—it is likely that the LTA-level enumeration technique will continue being exercised by a non-trivial subset of researchers. This is not a problem when the true number of latent classes remains constant over time, but forcing an invariant solution on non-invariant data is a legitimate possibility when the class configurations are not explicitly defined at each time point. Currently, it is unknown what consequences this type of LTA misspecification may have on model results.

The Monte Carlo simulation study presented here was designed to initiate this methodological conversation by describing how the misspecification of configural LMI to data with varying degrees of violations can impact LTA results such as class enumeration decisions and parameter recovery. Five different generating conditions were manipulated to produce 180 simulated “LTA realities” with violations to configural LMI across two time points:

- Pattern of configural non-invariance (i.e., three classes become four, or four classes become three);
- Within-class agreement/homogeneity and across-class separation;
- Magnitude of the non-invariant class prevalence split between Time 1 and Time 2;
- Overall sample size; and
- Transition matrix design (i.e., ordered or unordered).

Fitting a configurally invariant estimation model to data under these simulated conditions was expected to have obvious repercussions on class enumeration decisions—any solution with an equal number of latent classes estimated across time is technically incorrect, and the violation is compounded by constraining within-class item response parameters to equality at the two time points. Further, the forced blending of distinctly designed groups should produce model estimates (i.e., item response probabilities, class prevalence probabilities, and transition probabilities) that are markedly different from the true population values. The nature of these biases is summarized below.

KEY FINDINGS

Three-Class Solutions

Parameters from simulated data designed to produce a different number of highly homogenous and distinct latent classes at each time point were predictably difficult to recover, especially when a less complex model (i.e., three-class versus four-class solution) is estimated. For example, three-class solutions fit to data generated with Well-Defined class separation tended to underestimate within-class agreement on item responses for the non-invariant class at Time 1 (i.e., Class 3), combined with an interesting effect of also underestimating item agreement for Class 1. This may be partially explained by the impact that misspecification has on the transition probabilities for the third class: When the underlying data are designed with LMI Pattern A (i.e., three classes at Time 1 become four at Time 2), the probability of Class 3 members remaining in Class 3 is underestimated, and the probability of transitioning from Class 3 to Class 1 is symmetrically overestimated. That is, it seems that the Class 3 members designed to split into their own distinct class at Time 2, but who now have no fourth class to form, are aligning more with Class 1 than Class 3 over time. This is likely due to similarities in the generated logit thresholds for the first and third classes causing overlap in their respective mixture distributions. From a practitioner's viewpoint, this suggests that misspecified invariance can not only distort the interpretation of the non-invariant class(es), but the interpretation of the other classes, as well.

When the three-class models are fit to data generated under LMI Pattern B (i.e., four classes at Time 1 become three at Time 2), the impact on estimated within-class item agreement is less extreme than the bias seen under LMI Pattern A, particularly for the third latent class. The item parameters for the first latent class are still affected, though, with class agreement for the first two items being increasingly underestimated as the designed class prevalence split grows larger. This is reasonable when one considers the four distinct latent classes in the population at Time 1 that are forced to fit into three latent classes. When that fourth class is designed as a larger chunk of the merged classes at Time 2, and with less overlap in response patterns, trying to form three homogenous groups at Time 1 is likely to produce a set of classes that are substantively different from the four that comprise the population. It was not confirmed whether the classes estimated at Time 1 for these three-class models were similar to the three classes generated at Time 2, but that would be an interesting exploration.

While these misspecified, underfit models are not capturing the precise constitution and movement of the true latent classes over time, the somewhat aggregate story they tell could still align substantively within a particular research field. For example, a set of very nuanced substance use profiles could be present in the population during adolescence. Then, perhaps through maturation and the development of stronger social networks, two of those substance use profiles tend to start looking more like each other by early adulthood. By estimating an equal and symmetric set of latent classes at each time point, we might still produce naturally occurring substance use profiles, but they will not reflect the maximum homogeneity and separation that exists in the

population. The whole story cannot be told, and the field will not be advanced with potentially valuable information. It is helpful to remember that these three-class solutions with particularly offending levels of bias and convergence issues are fit to data that are much more likely to be assigned a best-fitting four-class solution in practice. In this way, the class enumeration procedure itself provides some protection against bias when the data are truly non-invariant.

Four-Class Solutions

The four-class solutions are all technically overfit and therefore provide a small increase in flexibility to estimate classes that are more homogenous than those estimated by three-class solutions fit to the same data. When three latent classes are generated at Time 1 (i.e., for LMI Pattern A), fitting four classes to that measurement occasion typically results in at least one estimated class that is smaller and more homogenous than designed. Under Well-Defined class separation conditions in this simulation, the affected class ends up being Class 1, and typically only when small sample sizes are generated. Again, this is likely due to similarities in generated logit thresholds for the first and third latent classes. Class 3 is more affected in the Poorly-Defined class separation conditions. When the Well-Defined class separation condition was accompanied by the High Thresholds, these models also produced some extreme overestimation of the standard errors for all estimated class prevalence parameters. These outliers are difficult to explain, but they could be impacted by the large standard deviations associated with high

logit threshold values. However, it is not clear why similar outliers aren't appearing in other high-threshold scenarios.

When four classes are generated *and* estimated at Time 1 (i.e., LMI Pattern B), there is almost no substantial bias in item response parameters associated with sample sizes of at least 500 and Well-Defined classes. Bias creeps in as the generated classes become less defined/separated, but is still mostly absent from $N = 1,000$ conditions.

Bias in the estimated transition probabilities provided by four-class solutions is predictably driven by the underlying pattern of non-invariance. If the data are generated with four classes merging into three, the transition probabilities for that fourth class reflect the new movement opportunity afforded by the extra class at Time 2. Conversely, when the data are generated with three classes splitting into four, transition probabilities for the third class are slightly impacted by losing members to the extra class estimated at Time 1.

In summary, while misspecification of configural invariance becomes less of a problem when a more complex k -class model is overfit to the data, it is inherently still failing to capture the true structural and measurement characteristics of the underlying data. However, it *is* estimating *one* true structure in the population—it is just not the best-fitting or most accurate structure.

RECOMMENDATIONS FOR PRACTICE

After considering the broad set of results produced by this simulation study, it should be clear that researchers should take the time to explore class enumeration at each

measurement occasion before forcing a symmetric, invariant LTA model on the data. Violations to longitudinal measurement invariance are likely to be rooted in some substantive context, and should be viewed as *interesting* problems to encounter. Such violations could inform researchers of nuanced movement in latent classes that they would otherwise not detect with a symmetrical, invariant LTA model. Further, a violation may indicate an inherent change in the respondents' interpretation of a survey item administered at multiple time points, which could prompt the redevelopment of a stronger scale. By imposing a symmetric LTA on data that are non-invariant in nature, the researcher is risking a complete misestimation of the number and type of latent classes that exist at a particular time point, particularly in terms of both under- and overestimated values of within-class agreement. When the inherent characteristics of each latent class's response patterns are misestimated, spurious profiles may be interpreted, and the transitions between these ill-defined profiles are therefore mostly trivial.

As is seen in the applied literature, there are a number of researchers that choose to make class enumeration decisions at the LTA level, presumably because they value the role of the autoregressive relationship in the estimation procedure. Testing the fit of asymmetric class solutions seems more likely to *follow* an exploration of time-specific LCA analyses that yield different class solutions, so assuming the LCAs are not run in advance, LTA-level class enumeration analysis are likely to be symmetric. If a researcher chooses to detect the best-fitting solution by comparing a set of configurally invariant k -class LTA models, it is hoped that they would give particular consideration to the AIC and ABIC suggestions, instead of BIC. As stated in an earlier chapter, BIC has been

proven to perform very well in class enumeration decisions with cross-sectional data (e.g., LCA), but tends to underfit when the estimated model is highly parameterized, as is seen with LTA. It seems reasonable to prefer an overfitted lens for analyzing non-invariant data, due to the added flexibility of the additional parameters estimated. However, as Dziak and colleagues (2017) succinctly stated in their assessment of IC performance, “*Sometimes the relative importance of sensitivity or specificity depends on the decisions to be made based on model predictions.*” If the estimation of few, large latent classes provides the most value and utility to the field, then an underfit model may be preferable, and BIC should be considered. Conversely, if it is more valuable for theoretical reasons to identify and explain as much heterogeneity in a sample as possible, an overfit solution is likely best.

STUDY LIMITATIONS AND FUTURE RESEARCH

This project provides just the tiniest glimpse into potential methods of exploring and quantifying the impact of violations to LMI in mixture models. There are numerous questions left unanswered, some more relevant to applied research than others. The specific line of research initiated by this dissertation would benefit from adding more nuanced levels to the manipulated study conditions, as the current set is quite limited in scope. For example, the variety in bias related to the size of the class prevalence split in the non-invariant class warrants further exploration, regarding both the direction and the magnitude of the split. Also, it would be interesting to manipulate the relationship between item parameters for the split/merged classes. Not enough thought was given to

designing logit thresholds for the invariant class, specifically, and it would be valuable to reassess the impact of class separation and agreement using population item parameters that are more likely to be found in empirical studies. It would also be worthwhile to explore the efficacy of the BLRT and LMR-LRT fit statistics at the overall LTA level, compared to the information criteria used in this study.

Attrition in survey respondents over time is a common issue for longitudinal research, so it would be interesting to model decreasing sample sizes at each measurement occasion. Additional, more complex types of violations to LMI need to be researched, perhaps introducing model covariates that have a direct impact on changing measurement properties (e.g., conditional transition probabilities). The simulation would also benefit from including results from “correct” model fitting conditions in all analyses.

Finally, an independent project may be warranted to polish the detection and correction algorithm for class label switching within the LTA framework. For example, using class prevalence probabilities as weights in the “distance” calculations would likely increase the precision of the measure. Future endeavors in LTA research may be spared from having to deal with the class label switching problem, however, as the latest version of *Mplus* (Version 8.5, released the day after this dissertation was defended) includes automatic reordering of latent classes for mixture models such as LCA and LTA.

Again, researchers are encouraged to thoroughly search for and define any patterns of longitudinal measurement non-invariance when embarking on an LTA, if not to inform the field of unusual transition patterns, but to ensure the selection of an appropriately fit estimation model. Running separate LCAs at each measurement

occasion is the preferable first step to this exploratory process. If time allows, a confirmatory class enumeration procedure could follow using the LTA-based approach. Assessing the risk of whether to overfit or underfit the number of classes estimated should be taken into consideration in the context of theory and the intended use of research results.

Appendix A: Parameter Recovery Tables

Table A.1. Three-Class Model Replication Counts Included in Analytical Sample

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	339	465	488	471	0
			500	392	487	499	496	0
			1000	446	499	500	498	0
		60/40	200	460	500	500	492	48
			500	493	500	500	500	2
			1000	498	500	500	500	0
		80/20	200	93	174	197	203	0
			500	77	138	159	214	0
			1000	63	102	123	221	0
	Unordered	50/50	200	374	485	497	473	0
			500	433	500	500	499	0
			1000	479	500	500	500	0
		60/40	200	471	500	500	496	267
			500	494	500	500	498	167
			1000	491	500	500	499	116
		80/20	200	140	218	260	253	0
			500	143	219	244	305	0
			1000	143	186	247	353	0
B	Ordered	50/50	200	370	491	497	485	0
			500	431	499	500	499	0
			1000	461	500	500	500	0
		60/40	200	428	497	500	491	4
			500	464	500	500	499	0
			1000	483	500	500	500	0
		80/20	200	468	500	500	497	161
			500	491	500	500	499	60
			1000	477	500	500	500	18
	Unordered	50/50	200	350	473	491	473	0
			500	385	495	500	498	0
			1000	436	500	500	500	0
		60/40	200	400	489	499	476	3
			500	451	500	500	499	0
			1000	472	500	500	498	0
		80/20	200	459	500	500	490	137
			500	490	500	500	500	42
			1000	484	500	500	499	10

Note. Analytical sample includes converged model replications with neither conflicting nor ghost class labels. LMI = longitudinal measurement invariance; WD = well-defined; PD = poorly-defined; LT = low thresholds; MT = moderate thresholds, HT = high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.2. Four-Class Model Replication Counts Included in Analytical Sample

LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Separation (via item response parameter patterns)				
				WD/LT	WD/MT	WD/HT	PD/MT	PD/HT
A	Ordered	50/50	200	368	410	289	271	298
			500	468	458	403	421	386
			1000	474	478	441	480	428
		60/40	200	185	415	290	121	301
			500	283	446	398	171	352
			1000	387	470	451	275	429
		80/20	200	434	388	324	440	330
			500	468	441	389	480	411
			1000	473	474	419	484	432
	Unordered	50/50	200	313	423	313	242	299
			500	439	470	432	357	397
			1000	483	492	476	457	454
		60/40	200	115	365	345	106	311
			500	137	475	430	95	388
			1000	233	488	479	156	445
		80/20	200	432	402	312	442	331
			500	468	467	413	489	413
			1000	477	479	447	486	456
B	Ordered	50/50	200	348	489	445	266	485
			500	451	482	499	401	498
			1000	469	484	498	454	499
		60/40	200	303	487	432	201	486
			500	427	480	499	329	496
			1000	470	478	498	440	498
		80/20	200	155	459	379	118	463
			500	236	485	494	136	496
			1000	372	492	498	208	498
	Unordered	50/50	200	364	495	486	270	486
			500	474	494	500	425	498
			1000	492	498	500	476	497
		60/40	200	319	492	471	207	485
			500	457	496	499	335	497
			1000	488	500	500	451	498
		80/20	200	159	456	424	131	472
			500	238	494	495	132	495
			1000	366	495	500	205	498

Note. Analytical sample includes converged model replications with no conflicting class labels. LMI = longitudinal measurement invariance; WD = well-defined; PD = poorly-defined; LT = low thresholds; MT = moderate thresholds, HT = high thresholds. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.3a. Item Response Parameter Recovery: Well-Defined Classes with Low Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
Ordered	50/50	200	339	0.14	0.15	-0.09	-0.09	-0.10	-0.06	-0.06	0.01	0.02	0.02	0.09	0.08	-0.11	-0.11	-0.11
		500	392	0.13	0.12	-0.06	-0.07	-0.05	0.05	0.04	0.02	0.02	0.02	0.08	0.08	-0.12	-0.12	-0.12
		1000	446	0.11	0.11	-0.04	-0.06	-0.05	0.07	0.07	0.02	0.02	0.03	0.08	0.08	-0.13	-0.13	-0.13
	60/40	200	460	0.05	0.05	-0.06	-0.07	-0.04	-0.10	-0.08	0.02	0.02	0.02	0.05	0.04	-0.06	-0.05	-0.05
		500	493	0.04	0.04	-0.01	-0.03	-0.02	-0.03	-0.02	0.02	0.02	0.02	0.03	0.03	-0.05	-0.05	-0.05
		1000	498	0.04	0.04	-0.01	-0.02	-0.01	0.00	0.00	0.02	0.02	0.02	0.03	0.03	-0.05	-0.05	-0.05
	80/20	200	93	0.62	0.62	-0.10	-0.11	-0.12	-0.22	-0.23	-0.01	-0.02	0.00	0.03	0.06	-0.02	0.01	-0.02
		500	77	0.69	0.68	-0.12	-0.14	-0.09	-0.19	-0.18	-0.05	-0.05	-0.05	0.05	0.04	0.00	0.00	-0.01
		1000	63	0.74	0.73	-0.11	-0.11	-0.10	-0.20	-0.20	-0.07	-0.07	-0.06	0.02	0.02	0.02	0.01	0.01
Unordered	50/50	200	374	0.13	0.14	-0.08	-0.09	-0.08	-0.08	-0.08	0.01	0.02	0.02	0.07	0.06	-0.09	-0.09	-0.09
		500	433	0.12	0.12	-0.05	-0.06	-0.04	0.02	0.02	0.02	0.01	0.02	0.07	0.07	-0.10	-0.09	-0.10
		1000	479	0.12	0.12	-0.04	-0.05	-0.04	0.04	0.04	0.02	0.02	0.02	0.06	0.06	-0.10	-0.10	-0.10
	60/40	200	471	0.03	0.04	-0.06	-0.07	-0.03	-0.12	-0.09	0.02	0.02	0.01	0.04	0.03	-0.03	-0.03	-0.03
		500	494	0.03	0.02	-0.01	-0.03	-0.01	-0.05	-0.04	0.01	0.01	0.02	0.02	0.02	-0.03	-0.03	-0.03
		1000	491	0.03	0.03	0.00	-0.02	-0.01	-0.02	-0.01	0.01	0.01	0.02	0.01	0.01	-0.03	-0.03	-0.03
	80/20	200	140	0.58	0.58	-0.11	-0.10	-0.10	-0.21	-0.22	-0.02	-0.02	-0.01	0.04	0.07	-0.03	0.01	-0.01
		500	143	0.63	0.61	-0.10	-0.11	-0.08	-0.16	-0.15	-0.04	-0.04	-0.04	0.05	0.05	0.00	-0.01	-0.01
		1000	143	0.70	0.70	-0.10	-0.10	-0.09	-0.19	-0.17	-0.06	-0.06	-0.06	0.03	0.02	0.02	0.01	0.02

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.3b. Item Response Parameter Recovery: Well-Defined Classes with Low Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
Ordered	50/50	200	370	0.22	0.22	-0.08	-0.08	-0.06	-0.10	-0.08	0.02	0.02	0.02	0.08	0.08	-0.07	-0.07	-0.07
		500	431	0.19	0.19	-0.06	-0.07	-0.05	-0.01	-0.01	0.01	0.01	0.01	0.07	0.07	-0.08	-0.08	-0.08
		1000	461	0.19	0.19	-0.05	-0.06	-0.05	0.01	0.01	0.01	0.01	0.01	0.06	0.06	-0.08	-0.08	-0.08
	60/40	200	428	0.14	0.15	-0.08	-0.08	-0.06	-0.09	-0.07	0.02	0.02	0.02	0.07	0.06	-0.07	-0.07	-0.07
		500	464	0.13	0.13	-0.04	-0.05	-0.04	-0.01	-0.01	0.02	0.02	0.02	0.05	0.05	-0.07	-0.07	-0.07
		1000	483	0.13	0.13	-0.03	-0.04	-0.04	0.01	0.01	0.02	0.02	0.02	0.04	0.05	-0.07	-0.07	-0.07
	80/20	200	468	0.06	0.06	-0.06	-0.07	-0.04	-0.09	-0.06	0.02	0.02	0.02	0.06	0.05	-0.04	-0.04	-0.04
		500	491	0.05	0.05	-0.02	-0.04	-0.02	-0.03	-0.02	0.02	0.02	0.02	0.03	0.03	-0.04	-0.04	-0.04
		1000	477	0.05	0.05	-0.01	-0.02	-0.02	-0.01	-0.01	0.02	0.02	0.02	0.02	0.02	-0.04	-0.04	-0.04
Unordered	50/50	200	350	0.20	0.21	-0.07	-0.07	-0.06	-0.11	-0.09	0.01	0.02	0.01	0.09	0.07	-0.08	-0.08	-0.08
		500	385	0.18	0.18	-0.06	-0.06	-0.05	-0.01	-0.01	0.01	0.01	0.01	0.07	0.07	-0.09	-0.09	-0.09
		1000	436	0.18	0.18	-0.05	-0.06	-0.05	0.02	0.01	0.01	0.01	0.01	0.06	0.06	-0.09	-0.09	-0.09
	60/40	200	400	0.14	0.14	-0.06	-0.05	-0.04	-0.09	-0.06	0.02	0.02	0.02	0.08	0.07	-0.07	-0.08	-0.07
		500	451	0.12	0.12	-0.04	-0.05	-0.03	-0.01	0.00	0.02	0.02	0.02	0.06	0.05	-0.08	-0.08	-0.08
		1000	472	0.12	0.12	-0.03	-0.04	-0.03	0.02	0.01	0.02	0.01	0.02	0.04	0.05	-0.08	-0.08	-0.08
	80/20	200	459	0.05	0.06	-0.05	-0.05	-0.02	-0.10	-0.07	0.02	0.02	0.02	0.06	0.04	-0.05	-0.04	-0.04
		500	490	0.05	0.04	-0.01	-0.02	0.00	-0.03	-0.02	0.02	0.02	0.02	0.03	0.03	-0.04	-0.04	-0.04
		1000	484	0.05	0.05	-0.01	-0.02	-0.01	0.00	-0.01	0.02	0.02	0.02	0.02	0.02	-0.04	-0.04	-0.04

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.4a. Item Response Parameter Recovery: Well-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Ordered	50/50	200	465	0.71	0.71	-0.09	-0.11	-0.07	0.03	0.05	0.00	0.00	0.00	0.03	0.03	-0.12	-0.11	-0.11
		500	487	0.67	0.67	-0.08	-0.10	-0.08	0.08	0.08	0.00	0.00	0.00	0.03	0.03	-0.12	-0.12	-0.12
		1000	499	0.67	0.66	-0.08	-0.09	-0.08	0.07	0.08	0.00	0.00	0.00	0.03	0.03	-0.12	-0.12	-0.12
	60/40	200	500	0.23	0.23	-0.04	-0.05	-0.01	-0.01	0.00	0.00	0.00	0.00	0.02	0.01	-0.06	-0.06	-0.06
		500	500	0.19	0.19	-0.02	-0.03	-0.02	0.02	0.03	0.01	0.00	0.01	0.02	0.01	-0.07	-0.07	-0.06
		1000	500	0.18	0.17	-0.02	-0.03	-0.02	0.02	0.03	0.01	0.00	0.01	0.01	0.01	-0.07	-0.07	-0.07
	80/20	200	174	2.44	2.41	-0.05	-0.05	-0.07	-0.17	-0.16	-0.02	-0.01	-0.01	0.02	0.03	-0.01	0.00	-0.01
		500	138	2.48	2.47	-0.05	-0.04	-0.04	-0.13	-0.14	-0.02	-0.02	-0.01	0.02	0.02	0.00	0.00	0.00
		1000	102	2.51	2.50	-0.03	-0.04	-0.03	-0.12	-0.11	-0.01	-0.01	-0.01	0.01	0.02	0.01	0.01	0.01
Unordered	50/50	200	485	0.69	0.70	-0.09	-0.10	-0.06	0.02	0.04	0.00	0.00	0.00	0.02	0.02	-0.09	-0.08	-0.09
		500	500	0.71	0.72	-0.08	-0.09	-0.08	0.05	0.07	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		1000	500	0.78	0.78	-0.09	-0.09	-0.08	0.03	0.04	0.00	0.00	0.00	0.02	0.02	-0.07	-0.07	-0.07
	60/40	200	500	0.20	0.20	-0.02	-0.05	0.00	-0.03	-0.01	0.00	0.00	0.00	0.01	0.00	-0.03	-0.03	-0.03
		500	500	0.19	0.19	-0.01	-0.03	-0.01	0.01	0.02	0.00	0.00	0.00	0.01	0.01	-0.03	-0.03	-0.03
		1000	500	0.19	0.18	-0.01	-0.02	-0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	-0.03	-0.03	-0.03
	80/20	200	218	2.28	2.26	-0.04	-0.04	-0.04	-0.14	-0.13	-0.01	-0.01	-0.01	0.02	0.02	-0.01	0.01	0.00
		500	219	2.28	2.27	-0.03	-0.02	-0.02	-0.09	-0.09	-0.01	-0.01	-0.01	0.02	0.02	0.00	0.00	0.00
		1000	186	2.29	2.29	-0.02	-0.02	-0.02	-0.09	-0.09	-0.01	-0.01	-0.01	0.01	0.01	0.01	0.01	0.01

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.4b. Item Response Parameter Recovery: Well-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Ordered	50/50	200	491	0.84	0.84	-0.10	-0.10	-0.07	-0.01	0.02	0.00	0.00	0.00	0.02	0.02	-0.09	-0.09	-0.09
		500	499	0.88	0.88	-0.09	-0.10	-0.09	0.02	0.03	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		1000	500	0.93	0.93	-0.09	-0.10	-0.09	0.00	0.02	0.00	0.00	0.00	0.02	0.02	-0.07	-0.07	-0.07
	60/40	200	497	0.63	0.63	-0.08	-0.08	-0.06	-0.02	0.01	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		500	500	0.63	0.63	-0.07	-0.08	-0.07	0.02	0.04	0.00	0.00	0.00	0.02	0.02	-0.07	-0.08	-0.07
		1000	500	0.67	0.67	-0.07	-0.08	-0.07	0.01	0.03	0.00	0.00	0.00	0.02	0.02	-0.07	-0.07	-0.07
	80/20	200	500	0.26	0.25	-0.04	-0.05	-0.02	-0.03	0.00	0.00	0.00	0.00	0.01	0.01	-0.05	-0.05	-0.05
		500	500	0.24	0.24	-0.03	-0.04	-0.03	0.01	0.03	0.00	0.00	0.00	0.01	0.01	-0.05	-0.05	-0.05
		1000	500	0.23	0.23	-0.03	-0.03	-0.02	0.01	0.02	0.00	0.00	0.00	0.01	0.01	-0.05	-0.05	-0.05
Unordered	50/50	200	473	0.80	0.80	-0.09	-0.10	-0.07	0.01	0.03	0.00	0.00	0.00	0.03	0.02	-0.09	-0.09	-0.09
		500	495	0.84	0.84	-0.09	-0.10	-0.09	0.04	0.05	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		1000	500	0.88	0.88	-0.09	-0.10	-0.09	0.02	0.03	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.07
	60/40	200	489	0.59	0.59	-0.07	-0.08	-0.05	0.01	0.04	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		500	500	0.61	0.61	-0.07	-0.08	-0.07	0.04	0.05	0.00	0.00	0.00	0.02	0.02	-0.08	-0.08	-0.08
		1000	500	0.63	0.63	-0.07	-0.08	-0.07	0.03	0.04	0.00	0.00	0.00	0.02	0.02	-0.07	-0.07	-0.07
	80/20	200	500	0.25	0.25	-0.04	-0.05	-0.01	-0.02	0.01	0.00	0.00	0.00	0.01	0.01	-0.05	-0.05	-0.05
		500	500	0.24	0.24	-0.02	-0.04	-0.02	0.03	0.04	0.00	0.00	0.00	0.01	0.01	-0.05	-0.05	-0.05
		1000	500	0.23	0.23	-0.02	-0.03	-0.02	0.03	0.04	0.00	0.00	0.01	0.01	0.01	-0.05	-0.05	-0.05

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.5a. Item Response Parameter Recovery: Well-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Ordered	50/50	200	488	3.46	3.44	-0.13	-0.11	-0.10	-0.03	-0.03	0.00	0.00	0.00	0.01	0.00	-0.06	-0.06	-0.06
		500	499	3.65	3.64	-0.10	-0.11	-0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.04	-0.04	-0.04
		1000	500	3.90	3.90	-0.12	-0.12	-0.11	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
	60/40	200	500	1.19	1.18	-0.07	-0.06	-0.05	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	-0.05	-0.05	-0.05
		500	500	1.17	1.17	-0.04	-0.06	-0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.05	-0.05	-0.05
		1000	500	1.20	1.20	-0.05	-0.05	-0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.04	-0.04	-0.04
	80/20	200	197	7.34	7.33	-0.01	-0.02	-0.04	-0.11	-0.13	0.00	-0.01	0.00	0.01	0.01	-0.01	0.00	-0.01
		500	159	7.29	7.31	-0.04	-0.04	0.00	-0.11	-0.12	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
		1000	123	7.23	7.23	-0.03	-0.01	0.00	-0.10	-0.11	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Unordered	50/50	200	497	3.13	3.12	-0.13	-0.10	-0.09	-0.02	-0.01	0.00	0.00	0.00	0.00	0.00	-0.04	-0.04	-0.04
		500	500	3.33	3.33	-0.10	-0.11	-0.10	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
		1000	500	3.45	3.45	-0.12	-0.11	-0.10	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
	60/40	200	500	0.93	0.92	-0.05	-0.04	-0.03	-0.03	-0.03	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
		500	500	1.03	1.03	-0.03	-0.05	-0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
		1000	500	1.07	1.08	-0.04	-0.04	-0.03	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01
	80/20	200	260	6.73	6.71	-0.03	-0.02	-0.03	-0.12	-0.12	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
		500	244	6.68	6.69	-0.03	-0.02	0.01	-0.08	-0.09	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
		1000	247	6.63	6.62	-0.02	0.00	0.01	-0.08	-0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.5b. Item Response Parameter Recovery: Well-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Ordered	50/50	200	497	3.39	3.38	-0.13	-0.10	-0.10	-0.05	-0.04	0.00	0.00	0.00	0.00	0.00	-0.05	-0.05	-0.04
		500	500	3.72	3.71	-0.10	-0.12	-0.10	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	3.83	3.84	-0.11	-0.11	-0.11	-0.02	-0.03	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
	60/40	200	500	2.68	2.67	-0.12	-0.10	-0.09	-0.04	-0.03	0.00	0.00	0.00	0.00	0.00	-0.04	-0.04	-0.04
		500	500	2.94	2.94	-0.10	-0.11	-0.10	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	3.11	3.12	-0.11	-0.11	-0.11	-0.01	-0.03	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
	80/20	200	500	1.22	1.20	-0.07	-0.06	-0.04	-0.03	-0.03	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		500	500	1.34	1.33	-0.05	-0.07	-0.05	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	1.40	1.40	-0.06	-0.06	-0.05	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
Unordered	50/50	200	491	3.20	3.20	-0.12	-0.10	-0.10	-0.02	-0.02	0.00	0.00	0.00	0.01	0.00	-0.05	-0.05	-0.05
		500	500	3.43	3.43	-0.10	-0.12	-0.10	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	3.64	3.64	-0.11	-0.12	-0.11	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
	60/40	200	499	2.53	2.52	-0.11	-0.10	-0.09	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.05	-0.04	-0.04
		500	500	2.75	2.74	-0.10	-0.11	-0.10	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	2.94	2.95	-0.11	-0.11	-0.11	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02
	80/20	200	500	1.16	1.15	-0.08	-0.06	-0.05	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		500	500	1.29	1.29	-0.05	-0.07	-0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.03
		1000	500	1.33	1.34	-0.06	-0.06	-0.05	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.02

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.6a. Item Response Parameter Recovery: Poorly-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50
Ordered	50/50	200	471	0.01	0.00	-0.05	0.01	-0.01	-0.03	-0.25	0.00	0.03	0.01	0.13	0.04	-0.17	1.71	-0.12
		500	496	0.01	-0.01	-0.04	0.01	-0.02	-0.02	-0.24	0.01	0.01	0.01	0.21	0.01	-0.18	2.47	-0.12
		1000	498	0.01	0.00	-0.04	0.01	-0.02	-0.01	-0.19	0.01	0.00	0.01	0.24	0.00	-0.18	2.58	-0.12
	60/40	200	492	0.01	0.00	-0.02	0.00	0.00	-0.03	-0.24	-0.01	0.05	0.01	0.02	0.03	-0.07	0.63	-0.05
		500	500	0.01	0.00	-0.02	0.00	0.00	-0.01	-0.15	0.00	0.01	0.00	0.06	0.01	-0.08	0.85	-0.05
		1000	500	0.01	0.00	-0.02	0.00	0.00	0.00	-0.12	0.00	0.01	0.00	0.08	0.00	-0.07	0.93	-0.05
	80/20	200	203	-0.01	-0.02	-0.15	-0.03	-0.06	-0.02	-0.30	0.00	0.07	0.00	0.08	0.04	-0.26	2.58	-0.14
		500	214	0.01	-0.02	-0.12	-0.01	-0.04	-0.02	-0.27	0.01	0.02	0.02	0.26	0.01	-0.32	3.95	-0.20
		1000	221	0.02	-0.01	-0.09	0.02	-0.04	-0.01	-0.20	0.02	0.00	0.02	0.46	0.01	-0.35	4.73	-0.23
Unordered	50/50	200	473	0.00	0.00	-0.05	0.01	-0.01	-0.02	-0.22	0.00	0.05	0.01	0.05	0.03	-0.14	1.58	-0.09
		500	499	0.01	-0.01	-0.04	0.00	-0.02	-0.01	-0.19	0.00	0.01	0.01	0.15	0.01	-0.15	2.03	-0.09
		1000	500	0.01	-0.01	-0.04	0.00	-0.02	-0.01	-0.15	0.00	0.01	0.00	0.18	0.00	-0.15	2.14	-0.09
	60/40	200	496	0.00	0.00	-0.02	0.00	0.01	-0.02	-0.23	-0.02	0.06	0.01	-0.03	0.02	-0.04	0.51	-0.03
		500	498	0.00	0.00	-0.01	-0.01	0.00	-0.01	-0.12	0.00	0.01	0.00	0.02	0.00	-0.04	0.52	-0.03
		1000	499	0.00	0.00	-0.01	0.00	0.00	0.00	-0.07	0.00	0.01	0.00	0.04	0.00	-0.04	0.56	-0.03
	80/20	200	253	-0.02	-0.01	-0.16	-0.03	-0.06	-0.02	-0.24	0.00	0.09	0.00	0.02	0.04	-0.22	2.28	-0.12
		500	305	0.00	-0.02	-0.11	-0.02	-0.04	-0.02	-0.23	0.01	0.03	0.01	0.22	0.00	-0.30	3.64	-0.18
		1000	353	0.02	-0.01	-0.09	0.01	-0.04	-0.01	-0.18	0.02	0.01	0.01	0.39	0.00	-0.32	4.51	-0.21

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.6b. Item Response Parameter Recovery: Poorly-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50
Ordered	50/50	200	485	0.01	-0.01	-0.07	-0.01	-0.02	-0.03	-0.27	-0.01	0.05	0.00	0.01	0.03	-0.15	1.30	-0.09
		500	499	0.01	-0.01	-0.06	-0.02	-0.02	-0.02	-0.18	0.00	0.02	0.00	0.07	0.00	-0.16	1.63	-0.09
		1000	500	0.01	-0.01	-0.06	-0.01	-0.02	-0.01	-0.14	0.00	0.01	0.00	0.09	0.00	-0.15	1.75	-0.09
	60/40	200	491	0.01	-0.01	-0.05	-0.01	-0.02	-0.03	-0.25	-0.01	0.05	0.01	0.00	0.03	-0.12	1.01	-0.07
		500	499	0.01	-0.01	-0.05	-0.01	-0.02	-0.02	-0.16	0.00	0.02	0.00	0.05	0.00	-0.13	1.26	-0.07
		1000	500	0.01	-0.01	-0.05	-0.01	-0.02	-0.01	-0.12	0.00	0.01	0.00	0.07	0.00	-0.12	1.33	-0.07
	80/20	200	497	0.01	0.00	-0.03	-0.01	0.00	-0.03	-0.25	-0.01	0.06	0.01	-0.03	0.02	-0.06	0.48	-0.04
		500	499	0.01	0.00	-0.02	-0.01	-0.01	-0.01	-0.13	0.00	0.02	0.00	0.01	0.00	-0.06	0.58	-0.04
		1000	500	0.01	0.00	-0.02	0.00	-0.01	-0.01	-0.09	0.00	0.01	0.00	0.03	0.00	-0.06	0.58	-0.04
Unordered	50/50	200	473	0.00	0.00	-0.06	0.00	-0.02	-0.03	-0.26	-0.01	0.08	0.00	0.05	0.02	-0.15	1.51	-0.09
		500	498	0.01	-0.01	-0.05	-0.01	-0.02	-0.01	-0.16	0.00	0.02	0.00	0.14	0.00	-0.16	1.89	-0.09
		1000	500	0.00	-0.01	-0.05	0.00	-0.02	0.00	-0.14	0.00	0.02	0.00	0.16	-0.01	-0.16	2.06	-0.09
	60/40	200	476	0.00	0.00	-0.05	0.00	-0.01	-0.03	-0.27	-0.01	0.07	0.01	0.05	0.03	-0.13	1.22	-0.07
		500	499	0.01	-0.01	-0.04	-0.01	-0.02	-0.01	-0.14	0.00	0.02	0.00	0.11	0.00	-0.13	1.44	-0.07
		1000	498	0.00	-0.01	-0.04	0.00	-0.01	0.00	-0.11	0.00	0.01	0.00	0.12	-0.01	-0.13	1.58	-0.08
	80/20	200	490	0.01	0.00	-0.02	0.00	0.00	-0.02	-0.25	-0.01	0.08	0.01	-0.01	0.01	-0.06	0.70	-0.03
		500	500	0.00	0.00	-0.02	0.00	-0.01	-0.01	-0.10	0.00	0.02	0.00	0.05	0.00	-0.07	0.74	-0.04
		1000	499	0.00	0.00	-0.02	0.00	0.00	0.00	-0.07	0.00	0.01	0.00	0.06	0.00	-0.06	0.77	-0.04

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.7a. Item Response Parameter Recovery: Poorly-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Parameters														
		Total Sample Size	Number Valid Reps	Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split			0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05
Ordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	48	0.00	-0.02	0.01	-0.03	-0.01	0.07	0.08	-0.05	-0.01	-0.03	6.77	-0.18	0.05	-0.08	-0.28
		500	2	-0.02	-0.05	0.03	-0.10	-0.11	-0.01	-0.06	-0.04	0.00	0.01	5.29	-0.11	0.20	-0.11	-0.18
		1000	0															
	80/20	200	0															
		500	0															
		1000	0															
Unordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	267	0.00	-0.04	0.02	-0.07	0.02	0.04	0.01	0.02	-0.01	-0.03	1.81	-0.06	-0.02	-0.02	-0.10
		500	167	0.00	-0.05	0.02	-0.05	0.00	0.02	0.00	0.01	0.01	-0.01	0.39	-0.04	0.01	-0.02	-0.04
		1000	116	0.00	-0.05	0.02	-0.05	0.02	-0.01	0.01	0.00	0.00	-0.01	0.44	-0.02	0.02	-0.01	-0.03
	80/20	200	0															
		500	0															
		1000	0															

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.7b. Item Response Parameter Recovery: Poorly-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
				0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05
Ordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	4	-0.01	-0.14	0.00	-0.06	-0.08	-0.06	0.06	0.05	-0.04	-0.02	-1.00	-0.15	-0.34	-0.06	-0.18
		500	0															
		1000	0															
	80/20	200	161	0.00	-0.07	0.02	-0.08	-0.05	0.09	0.03	0.03	-0.01	-0.01	0.74	-0.06	-0.01	-0.02	-0.09
		500	60	0.00	-0.08	0.03	-0.08	-0.04	0.05	0.02	0.01	0.01	0.00	-0.17	-0.06	0.05	-0.02	-0.05
		1000	18	0.01	-0.08	0.02	-0.07	0.00	-0.03	0.04	0.00	0.01	0.00	-0.58	-0.04	0.05	-0.03	-0.08
Unordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	3	-0.02	-0.14	-0.04	-0.08	0.01	0.04	0.10	0.08	-0.04	-0.02	-1.00	-0.09	-0.36	-0.09	-0.08
		500	0															
		1000	0															
	80/20	200	137	0.00	-0.06	0.02	-0.02	-0.03	0.10	0.04	0.04	-0.01	-0.02	1.81	-0.08	0.00	-0.03	-0.11
		500	42	0.00	-0.07	0.03	-0.08	-0.04	0.03	0.01	-0.01	0.01	0.00	0.60	-0.07	0.07	-0.02	-0.07
		1000	10	0.00	-0.07	0.02	-0.05	0.02	0.05	0.07	0.00	0.00	0.00	-0.56	-0.06	0.04	-0.03	-0.03

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.8a. Item Response Parameter Recovery: Well-Defined Classes with Low Thresholds, Four-Class Solutions, Non-Invariance
Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	368	-0.17	-0.21	-0.03	-0.06	-0.04	-0.11	-0.09	0.01	0.01	0.02	0.04	0.04	0.04	0.05	0.04	--	--	--	--	--
		500	468	-0.08	-0.09	0.00	-0.03	-0.01	-0.01	-0.01	0.00	0.01	0.01	0.03	0.03	0.03	0.02	0.02	--	--	--	--	--
		1000	474	-0.05	-0.06	0.00	-0.02	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	--	--	--	--	--
	60/40	200	185	-0.19	-0.19	-0.06	-0.06	-0.06	-0.16	-0.09	-0.01	0.01	0.00	0.01	0.02	0.05	0.07	0.06	--	--	--	--	--
		500	283	-0.11	-0.17	-0.02	-0.04	-0.02	-0.05	-0.01	0.01	0.01	0.01	0.03	0.02	0.03	0.03	0.03	--	--	--	--	--
		1000	387	-0.07	-0.08	-0.01	-0.03	-0.01	-0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	--	--	--	--	--
	80/20	200	434	-0.15	-0.14	-0.03	-0.07	-0.02	-0.14	-0.13	0.01	0.02	0.01	0.01	0.01	0.04	0.03	0.02	--	--	--	--	--
		500	468	-0.07	-0.08	0.00	-0.03	-0.01	-0.03	-0.03	0.00	0.01	0.01	0.01	0.02	0.01	0.02	0.01	--	--	--	--	--
		1000	473	-0.05	-0.05	0.00	-0.02	0.00	-0.02	-0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	--	--	--	--	--
Unordered	50/50	200	313	-0.19	-0.22	-0.02	-0.06	-0.02	-0.10	-0.08	0.00	0.02	0.02	0.04	0.03	0.04	0.06	0.05	--	--	--	--	--
		500	439	-0.09	-0.12	0.00	-0.03	-0.01	-0.02	-0.01	0.00	0.00	0.01	0.03	0.03	0.03	0.03	0.03	--	--	--	--	--
		1000	483	-0.06	-0.06	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01	--	--	--	--	--
	60/40	200	115	-0.17	-0.24	-0.07	-0.07	-0.06	-0.23	-0.10	-0.01	0.00	0.01	0.05	-0.01	0.04	0.08	0.07	--	--	--	--	--
		500	137	-0.13	-0.15	-0.03	-0.02	-0.02	-0.06	-0.02	0.01	0.00	0.01	0.01	0.00	0.04	0.04	0.03	--	--	--	--	--
		1000	233	-0.08	-0.15	0.00	-0.02	-0.01	-0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.02	--	--	--	--	--
	80/20	200	432	-0.16	-0.18	-0.03	-0.07	-0.01	-0.14	-0.13	0.01	0.02	0.01	0.01	0.01	0.04	0.03	0.02	--	--	--	--	--
		500	468	-0.08	-0.08	0.00	-0.03	0.00	-0.01	-0.01	0.00	0.01	0.01	0.02	0.02	0.02	0.02	0.01	--	--	--	--	--
		1000	477	-0.05	-0.05	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.8b. Item Response Parameter Recovery: Well-Defined Classes with Low Thresholds, Four-Class Solutions, Non-Invariance
Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.27	0.27	0.27
Ordered	50/50	200	348	-0.17	-0.20	-0.05	-0.05	-0.02	-0.14	-0.09	0.01	0.01	0.02	0.04	0.03	0.04	0.04	0.04	0.01	0.04	-0.01	-0.01	0.00
		500	451	-0.09	-0.10	-0.01	-0.03	0.00	-0.02	-0.01	0.01	0.01	0.01	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.01
		1000	469	-0.05	-0.06	0.00	-0.02	0.00	-0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.03	0.01
	60/40	200	303	-0.19	-0.20	-0.02	-0.05	-0.02	-0.14	-0.09	0.01	0.02	0.02	0.04	0.03	0.04	0.05	0.04	0.02	0.02	0.03	0.03	0.06
		500	427	-0.09	-0.13	-0.01	-0.04	-0.01	-0.02	0.00	0.00	0.01	0.01	0.03	0.02	0.02	0.02	0.03	0.00	0.03	0.02	0.03	0.02
		1000	470	-0.06	-0.06	0.00	-0.01	0.00	-0.01	-0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.01	0.02	0.04	0.01
	80/20	200	155	-0.19	-0.25	-0.02	-0.08	-0.04	-0.18	-0.07	-0.01	0.01	0.02	0.03	0.02	0.07	0.05	0.05	-0.01	0.04	0.05	0.09	0.05
		500	236	-0.13	-0.15	-0.01	-0.02	-0.02	-0.04	-0.03	0.00	0.00	0.01	0.03	0.02	0.03	0.03	0.03	0.00	0.02	-0.02	0.02	0.01
		1000	372	-0.08	-0.09	0.00	-0.02	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.02	0.02	0.03	-0.03
Unordered	50/50	200	364	-0.18	-0.22	-0.04	-0.04	-0.02	-0.19	-0.07	0.01	0.02	0.02	0.05	0.01	0.04	0.05	0.04	0.00	0.03	0.00	-0.01	0.00
		500	474	-0.08	-0.10	0.01	-0.02	0.01	-0.04	-0.04	0.00	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.00
		1000	492	-0.05	-0.06	0.01	0.00	0.01	-0.01	-0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.02	0.00
	60/40	200	319	-0.21	-0.22	-0.02	-0.05	-0.03	-0.14	-0.09	0.01	0.03	0.02	0.05	0.02	0.04	0.06	0.04	0.00	0.02	0.04	0.01	0.05
		500	457	-0.09	-0.12	0.00	-0.02	0.01	-0.05	-0.02	0.00	0.01	0.01	0.02	0.01	0.02	0.02	0.03	0.00	0.03	0.02	0.02	0.00
		1000	488	-0.05	-0.06	0.01	0.00	0.01	-0.01	-0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.01	0.02	0.03	0.00
	80/20	200	159	-0.22	-0.22	0.00	-0.08	-0.03	-0.17	-0.08	-0.01	0.01	0.01	0.03	0.02	0.06	0.07	0.06	0.04	-0.02	0.12	-0.01	0.04
		500	238	-0.13	-0.18	0.00	-0.01	0.00	-0.04	-0.04	0.00	0.00	0.01	0.02	0.02	0.03	0.03	0.03	-0.02	0.03	0.00	0.01	0.02
		1000	366	-0.09	-0.10	0.01	0.00	0.01	-0.01	-0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.02	-0.01	0.00	0.04	0.04	-0.01

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.9a. Item Response Parameter Recovery: Well-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																				
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities					
				0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	N/A	N/A	N/A	N/A	N/A	
Ordered	50/50	200	410	-0.05	-0.05	-0.01	-0.04	0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	--	--	--	--	--	
		500	458	-0.03	-0.04	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	478	-0.02	-0.02	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
	60/40	200	415	-0.07	-0.08	-0.02	-0.05	0.00	-0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	--	--	--	--	--	
		500	446	-0.04	-0.03	0.00	-0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	470	-0.02	-0.02	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
	80/20	200	388	-0.05	-0.05	-0.02	-0.03	0.00	-0.05	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	441	-0.03	-0.04	0.00	-0.01	0.00	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	474	-0.02	-0.03	0.00	-0.01	0.00	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
Unordered	50/50	200	423	-0.06	-0.06	-0.01	-0.03	0.01	-0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	--	--	--	--	--	
		500	470	-0.03	-0.04	0.00	-0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	492	-0.02	-0.03	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
	60/40	200	365	-0.12	-0.13	-0.02	-0.04	-0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	--	--	--	--	--	
		500	475	-0.05	-0.06	0.01	-0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	488	-0.02	-0.03	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
	80/20	200	402	-0.06	-0.06	0.00	-0.03	0.02	-0.04	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	--	--	--	--	--	
		500	467	-0.03	-0.03	0.01	-0.01	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	
		1000	479	-0.02	-0.03	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--	

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.9b. Item Response Parameter Recovery: Well-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.12	0.12	0.12
Ordered	50/50	200	489	-0.06	-0.06	-0.02	-0.03	0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.02
		500	482	-0.04	-0.04	0.00	-0.01	0.00	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00
		1000	484	-0.03	-0.03	0.00	0.00	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00
	60/40	200	487	-0.06	-0.07	-0.02	-0.02	0.01	-0.05	-0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.09	0.06	0.05
		500	480	-0.04	-0.04	0.00	-0.01	0.01	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00
		1000	478	-0.02	-0.03	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
	80/20	200	459	-0.08	-0.09	-0.02	-0.03	0.00	-0.04	-0.02	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	-0.01	-0.01	0.18	0.24	0.19
		500	485	-0.04	-0.05	0.00	-0.01	0.00	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	-0.03
		1000	492	-0.03	-0.03	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	-0.01
Unordered	50/50	200	495	-0.05	-0.06	-0.01	-0.02	0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.05	0.03
		500	494	-0.03	-0.03	0.00	-0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00
		1000	498	-0.02	-0.02	0.01	0.00	0.01	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00
	60/40	200	492	-0.06	-0.06	-0.01	-0.02	0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.06	0.06	0.03
		500	496	-0.03	-0.03	0.01	-0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	-0.01
		1000	500	-0.02	-0.02	0.01	0.00	0.01	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
	80/20	200	456	-0.10	-0.11	-0.01	-0.03	0.01	-0.04	-0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	-0.02	-0.02	0.22	0.20	0.23
		500	494	-0.04	-0.04	0.00	-0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.07	-0.01
		1000	495	-0.02	-0.03	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	-0.01

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.10a. Item Response Parameter Recovery: Well-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance
Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																				
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities					
				0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	N/A	N/A	N/A	N/A	N/A	
Ordered	50/50	200	289	-0.01	-0.01	-0.03	0.00	0.00	-0.06	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	403	-0.02	-0.03	0.01	-0.01	0.00	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	441	-0.02	-0.02	0.00	0.00	0.01	-0.02	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
	60/40	200	290	-0.04	-0.04	0.00	-0.01	0.00	-0.05	-0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	398	-0.02	-0.03	0.00	-0.01	0.01	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	451	-0.02	-0.03	0.00	0.00	0.01	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
	80/20	200	324	-0.04	-0.04	-0.01	-0.03	-0.01	-0.04	-0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	389	-0.01	-0.03	0.01	0.00	0.01	-0.03	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	419	-0.02	-0.02	0.01	-0.01	0.01	-0.02	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
Unordered	50/50	200	313	-0.03	-0.06	0.00	-0.03	0.01	-0.04	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	432	-0.01	-0.03	0.01	-0.01	0.02	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	476	-0.02	-0.02	0.00	0.00	0.01	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
	60/40	200	345	-0.08	-0.05	-0.01	-0.04	0.01	-0.05	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	430	-0.03	-0.04	0.02	-0.01	0.02	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	479	-0.02	-0.02	0.00	0.00	0.01	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
	80/20	200	312	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02	-0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		500	413	-0.01	-0.02	0.01	-0.01	0.01	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
		1000	447	-0.02	-0.02	0.00	0.00	0.01	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.10b. Item Response Parameter Recovery: Well-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.05	0.05	0.05
Ordered	50/50	200	445	-0.01	-0.04	-0.02	0.00	0.02	-0.04	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.02	0.03
		500	499	-0.03	-0.04	0.01	-0.01	0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.01	-0.01
		1000	498	-0.03	-0.03	0.00	0.00	0.01	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	-0.02
	60/40	200	432	-0.01	-0.02	-0.02	-0.01	0.02	-0.04	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.08	0.10
		500	499	-0.03	-0.04	0.00	-0.01	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	0.00
		1000	498	-0.03	-0.03	0.00	0.00	0.01	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	-0.01
	80/20	200	379	-0.03	-0.05	-0.01	-0.01	0.02	-0.05	-0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.34	0.31	0.32
		500	494	-0.03	-0.04	0.01	-0.01	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.07	0.01
		1000	498	-0.03	-0.03	0.00	0.00	0.01	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	-0.02
Unordered	50/50	200	486	-0.02	-0.04	-0.02	-0.01	0.00	-0.02	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.02	0.04
		500	500	-0.02	-0.03	0.01	-0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.01	-0.01
		1000	500	-0.02	-0.02	0.01	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.02	-0.01
	60/40	200	471	-0.03	-0.04	-0.02	-0.01	0.00	-0.02	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.07	0.08
		500	499	-0.02	-0.03	0.01	-0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.03	0.00
		1000	500	-0.02	-0.02	0.01	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.03	-0.01
	80/20	200	424	-0.06	-0.07	-0.04	-0.01	0.00	-0.02	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.31	0.32	0.29
		500	495	-0.03	-0.04	0.01	-0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.08	0.02
		1000	500	-0.02	-0.02	0.01	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	-0.02

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.11a. Item Response Parameter Recovery: Poorly-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	271	0.02	0.00	0.10	0.03	0.04	-0.03	-0.34	-0.01	0.05	0.03	-0.28	0.09	0.23	0.17	0.08	--	--	--	--	--
		500	421	0.02	0.00	0.04	0.00	0.02	-0.01	-0.21	0.01	0.02	0.02	-0.17	0.01	0.10	-0.05	0.04	--	--	--	--	--
		1000	480	0.01	0.00	0.02	0.00	0.02	0.00	-0.09	0.01	0.01	0.01	-0.09	0.00	0.05	-0.20	0.02	--	--	--	--	--
	60/40	200	121	0.02	-0.01	0.11	0.04	0.03	-0.06	-0.41	0.01	0.07	0.03	-0.21	0.02	0.18	0.21	0.08	--	--	--	--	--
		500	171	0.02	0.00	0.05	0.00	0.01	-0.01	-0.18	0.01	0.01	0.03	-0.16	0.02	0.11	-0.20	0.02	--	--	--	--	--
		1000	275	0.01	0.00	0.04	0.01	0.02	0.00	-0.08	0.01	0.01	0.02	-0.08	0.00	0.05	-0.21	0.03	--	--	--	--	--
	80/20	200	440	0.03	0.00	0.07	0.00	0.04	-0.03	-0.34	0.01	0.08	0.03	-0.25	0.01	0.11	0.26	0.04	--	--	--	--	--
		500	480	0.02	0.00	0.03	0.00	0.02	-0.01	-0.17	0.01	0.02	0.02	-0.13	0.00	0.05	-0.08	0.02	--	--	--	--	--
		1000	484	0.01	0.00	0.02	0.00	0.01	0.00	-0.09	0.01	0.01	0.01	-0.06	0.00	0.03	-0.18	0.01	--	--	--	--	--
Unordered	50/50	200	242	0.02	0.01	0.08	0.05	0.04	-0.05	-0.41	0.01	0.08	0.04	-0.24	0.06	0.20	0.42	0.08	--	--	--	--	--
		500	357	0.02	0.00	0.05	0.00	0.02	-0.01	-0.21	0.01	0.02	0.02	-0.19	0.02	0.11	-0.02	0.05	--	--	--	--	--
		1000	457	0.01	0.00	0.03	0.00	0.02	0.00	-0.08	0.01	0.01	0.01	-0.11	0.00	0.06	-0.22	0.03	--	--	--	--	--
	60/40	200	106	0.02	-0.01	0.09	0.04	0.05	-0.02	-0.52	0.02	0.06	0.03	-0.22	0.05	0.26	0.29	0.09	--	--	--	--	--
		500	95	0.02	0.01	0.05	0.01	0.01	-0.01	-0.14	0.02	0.01	0.02	-0.17	0.01	0.10	-0.11	0.03	--	--	--	--	--
		1000	156	0.01	0.00	0.04	0.01	0.02	0.00	-0.08	0.01	0.02	0.02	-0.07	0.00	0.05	-0.19	0.04	--	--	--	--	--
	80/20	200	442	0.02	0.00	0.08	0.00	0.04	-0.04	-0.31	0.01	0.09	0.03	-0.23	0.02	0.13	0.19	0.05	--	--	--	--	--
		500	489	0.01	0.00	0.03	0.00	0.02	-0.01	-0.15	0.01	0.02	0.02	-0.15	0.00	0.05	-0.12	0.03	--	--	--	--	--
		1000	486	0.01	0.00	0.02	0.00	0.01	0.00	-0.06	0.01	0.01	0.01	-0.07	0.00	0.04	-0.21	0.02	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.11b. Item Response Parameter Recovery: Poorly-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50	0.50	0.40	0.05	0.21	0.21
Ordered	50/50	200	266	0.03	0.01	0.08	0.01	0.03	-0.05	-0.39	0.01	0.05	0.03	-0.22	0.07	0.18	-0.09	0.07	-0.04	0.02	0.38	0.00	0.02
		500	401	0.02	0.00	0.03	0.00	0.02	-0.02	-0.17	0.02	0.02	0.02	-0.12	0.00	0.07	-0.27	0.05	-0.02	0.01	0.40	0.01	-0.04
		1000	454	0.01	0.00	0.02	0.00	0.01	0.00	-0.09	0.01	0.02	0.01	-0.08	0.00	0.04	-0.36	0.03	-0.01	0.00	0.18	-0.01	-0.01
	60/40	200	201	0.03	-0.01	0.09	0.02	0.04	-0.06	-0.40	0.01	0.04	0.03	-0.24	0.07	0.18	-0.13	0.06	0.00	0.03	0.37	0.09	0.06
		500	329	0.02	0.00	0.04	0.01	0.01	-0.02	-0.16	0.02	0.03	0.02	-0.13	0.00	0.07	-0.29	0.05	0.00	0.00	0.55	0.01	-0.03
		1000	440	0.02	0.00	0.02	0.00	0.01	-0.01	-0.07	0.01	0.02	0.01	-0.07	0.00	0.04	-0.38	0.03	-0.02	0.00	0.26	-0.01	-0.03
	80/20	200	118	0.03	0.00	0.10	0.05	0.02	-0.10	-0.40	0.03	0.04	0.04	-0.17	0.03	0.12	-0.24	0.07	-0.01	0.07	1.03	0.10	0.07
		500	136	0.02	0.00	0.05	0.01	0.01	-0.02	-0.16	0.02	0.03	0.04	-0.15	-0.02	0.09	-0.30	0.03	-0.02	0.05	0.92	0.11	0.00
		1000	208	0.02	0.00	0.04	0.01	0.01	-0.01	-0.07	0.01	0.02	0.02	-0.07	0.00	0.04	-0.32	0.03	0.01	0.07	0.47	0.04	-0.06
Unordered	50/50	200	270	0.02	0.01	0.10	0.02	0.03	-0.05	-0.33	0.02	0.08	0.04	-0.18	0.04	0.16	-0.11	0.07	-0.02	0.06	0.51	0.00	-0.04
		500	425	0.02	0.00	0.05	0.00	0.01	0.00	-0.16	0.02	0.03	0.02	-0.13	0.00	0.10	-0.15	0.06	-0.02	0.03	0.38	-0.01	-0.02
		1000	476	0.01	0.00	0.02	0.00	0.01	0.00	-0.07	0.01	0.02	0.01	-0.08	0.00	0.05	-0.26	0.03	-0.01	0.00	0.18	-0.02	-0.02
	60/40	200	207	0.03	0.00	0.09	0.04	0.04	-0.05	-0.28	0.02	0.07	0.04	-0.17	0.03	0.18	0.06	0.10	-0.02	0.02	0.76	0.04	-0.05
		500	335	0.02	0.00	0.05	0.00	0.01	0.00	-0.16	0.02	0.03	0.03	-0.15	0.00	0.11	-0.14	0.06	-0.03	0.02	0.60	0.01	0.02
		1000	451	0.01	0.00	0.03	0.00	0.01	0.00	-0.07	0.01	0.02	0.01	-0.08	0.00	0.05	-0.31	0.03	-0.01	0.00	0.30	0.00	0.01
	80/20	200	131	0.03	0.00	0.14	0.02	0.06	-0.07	-0.45	0.04	0.10	0.05	-0.17	0.03	0.16	0.00	0.10	-0.03	0.11	1.38	0.11	-0.01
		500	132	0.02	-0.01	0.07	0.00	0.01	0.01	-0.08	0.03	0.02	0.03	-0.20	-0.02	0.10	-0.25	0.05	0.00	0.04	0.68	0.22	0.05
		1000	205	0.01	0.00	0.04	0.01	0.01	0.00	-0.08	0.02	0.02	0.02	-0.07	0.00	0.06	-0.25	0.04	0.00	0.03	0.60	0.06	-0.08

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.12a. Item Response Parameter Recovery: Poorly-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance
Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	298	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	-0.40	0.01	-0.06	0.00	-0.07	--	--	--	--	--
		500	386	0.00	0.00	0.00	-0.01	0.01	0.00	0.01	0.00	0.00	0.00	-0.44	0.00	-0.03	0.00	-0.02	--	--	--	--	--
		1000	428	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	-0.32	-0.01	-0.01	0.00	-0.01	--	--	--	--	--
	60/40	200	301	0.00	0.00	0.00	-0.04	0.01	-0.01	0.02	0.00	0.01	0.00	-0.52	-0.01	-0.04	0.00	-0.09	--	--	--	--	--
		500	352	0.00	0.00	0.00	-0.02	0.01	0.01	0.01	0.00	0.00	0.00	-0.42	-0.01	-0.01	0.00	-0.02	--	--	--	--	--
		1000	429	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	-0.34	0.00	-0.01	0.00	-0.01	--	--	--	--	--
	80/20	200	330	0.00	0.00	0.00	-0.01	0.03	-0.01	0.01	0.00	0.00	0.00	-0.41	0.00	-0.04	0.01	-0.03	--	--	--	--	--
		500	411	0.00	0.00	0.00	-0.01	0.01	0.00	0.01	0.00	0.00	0.00	-0.34	0.00	-0.01	0.00	-0.01	--	--	--	--	--
		1000	432	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	-0.21	0.00	-0.01	0.00	-0.01	--	--	--	--	--
Unordered	50/50	200	299	0.00	0.00	-0.01	-0.03	0.02	0.00	-0.01	0.00	0.00	0.00	-0.45	0.00	-0.07	0.01	-0.08	--	--	--	--	--
		500	397	0.00	0.00	0.00	-0.01	0.02	0.01	0.01	0.00	0.00	0.00	-0.39	-0.01	-0.02	0.00	-0.02	--	--	--	--	--
		1000	454	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	-0.28	-0.01	-0.01	0.00	-0.01	--	--	--	--	--
	60/40	200	311	0.00	0.00	0.00	0.00	0.01	-0.02	0.01	0.01	0.01	0.00	-0.33	0.00	-0.08	0.01	-0.09	--	--	--	--	--
		500	388	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	-0.42	-0.01	-0.02	0.00	-0.02	--	--	--	--	--
		1000	445	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	-0.30	-0.01	0.00	0.00	-0.01	--	--	--	--	--
	80/20	200	331	0.00	0.00	0.00	-0.02	0.02	-0.01	0.01	0.00	0.00	0.00	-0.38	0.01	-0.04	0.00	-0.03	--	--	--	--	--
		500	413	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	-0.37	0.00	-0.02	0.00	-0.01	--	--	--	--	--
		1000	456	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	-0.25	0.00	-0.01	0.00	-0.01	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.12b. Item Response Parameter Recovery: Poorly-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance
Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Parameters																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05	0.82	0.01	0.99	0.01	0.01
Ordered	50/50	200	485	0.00	0.00	0.00	0.00	0.04	-0.08	0.01	-0.02	0.00	0.00	-0.60	-0.01	-0.07	0.01	-0.16	0.00	3.20	0.00	0.22	1.25
		500	498	0.00	0.00	0.00	0.00	0.01	-0.06	0.01	-0.01	0.00	0.00	-0.56	-0.01	-0.06	0.00	-0.12	0.00	2.35	0.00	0.18	0.59
		1000	499	0.00	0.00	0.00	0.00	0.01	-0.05	0.01	-0.01	0.00	0.00	-0.49	-0.01	-0.05	0.00	-0.10	0.00	1.84	0.00	0.02	0.36
	60/40	200	486	0.00	0.00	0.00	0.00	0.03	-0.08	0.01	-0.02	0.00	0.00	-0.63	-0.01	-0.08	0.01	-0.16	-0.01	4.13	0.00	0.37	1.71
		500	496	0.00	0.00	0.00	0.00	0.01	-0.06	0.01	-0.02	0.00	0.00	-0.57	-0.01	-0.06	0.00	-0.12	0.00	3.12	0.00	0.19	0.86
		1000	498	0.00	0.00	0.00	0.00	0.01	-0.06	0.01	-0.01	0.00	0.00	-0.50	-0.01	-0.05	0.00	-0.10	0.00	2.45	0.00	0.04	0.52
	80/20	200	463	0.00	0.00	0.00	0.00	0.03	-0.07	0.02	-0.01	0.00	0.00	-0.57	-0.01	-0.08	0.01	-0.14	-0.01	8.05	-0.01	2.21	4.22
		500	496	0.00	0.00	0.00	0.00	0.01	-0.06	0.01	-0.01	0.00	0.00	-0.50	-0.01	-0.06	0.00	-0.09	-0.01	5.63	-0.01	0.59	1.71
		1000	498	0.00	0.00	0.00	0.00	0.01	-0.05	0.01	-0.01	0.00	0.00	-0.45	-0.01	-0.05	0.00	-0.08	-0.01	4.48	0.00	0.30	0.90
Unordered	50/50	200	486	0.00	0.00	0.00	0.00	0.04	-0.07	0.00	-0.01	0.00	0.00	-0.47	0.00	-0.07	0.01	-0.15	0.00	3.50	0.00	0.22	1.26
		500	498	0.00	0.00	0.00	0.00	0.01	-0.05	0.01	-0.01	0.00	0.00	-0.48	-0.01	-0.06	0.00	-0.10	0.00	2.51	0.00	0.15	0.58
		1000	497	0.00	0.00	0.00	0.00	0.01	-0.04	0.01	-0.01	0.00	0.00	-0.43	-0.01	-0.05	0.00	-0.09	0.00	1.87	0.00	0.00	0.32
	60/40	200	485	0.00	0.00	0.00	0.00	0.04	-0.06	0.02	-0.01	0.00	0.00	-0.50	-0.01	-0.07	0.01	-0.15	0.00	4.55	0.00	0.46	1.67
		500	497	0.00	0.00	0.00	0.00	0.01	-0.05	0.02	-0.01	0.00	0.00	-0.51	-0.02	-0.06	0.00	-0.10	0.00	3.15	0.00	0.20	0.79
		1000	498	0.00	0.00	0.00	0.00	0.01	-0.05	0.01	-0.01	0.00	0.00	-0.46	-0.01	-0.04	0.00	-0.09	0.00	2.52	0.00	-0.01	0.44
	80/20	200	472	0.00	0.00	0.00	0.00	0.04	-0.05	0.02	-0.01	0.00	0.00	-0.42	-0.01	-0.07	0.01	-0.13	-0.01	9.83	-0.01	2.34	4.81
		500	495	0.00	0.00	0.00	0.00	0.01	-0.04	0.01	-0.01	0.00	0.00	-0.46	-0.01	-0.05	0.00	-0.08	0.00	6.18	-0.01	0.57	1.58
		1000	498	0.00	0.00	0.00	0.00	0.01	-0.04	0.01	-0.01	0.00	0.00	-0.40	-0.01	-0.04	0.00	-0.07	-0.01	4.67	0.00	0.21	0.90

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.13a. Latent Class Prevalence Parameter Recovery: LMI Pattern A, Three-Class Solutions

Absolute Bias in Estimated Class Prevalence Parameters										
				Ordered Transition Pattern			Unordered Transition Pattern			
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	C1#1	C1#2	C1#3	Number Valid Reps	C1#1	C1#2	C1#3
Well-Defined, Low Thresholds	50/50	200	339	-0.02	0.05	-0.03	374	-0.02	0.04	-0.02
		500	392	-0.02	0.06	-0.04	433	-0.02	0.05	-0.03
		1000	446	-0.02	0.07	-0.05	479	-0.01	0.05	-0.04
	60/40	200	460	-0.01	0.01	0.00	471	-0.01	0.01	0.00
		500	493	-0.01	0.01	-0.01	494	0.00	0.00	0.00
		1000	498	0.00	0.01	-0.01	491	0.00	0.00	0.00
	80/20	200	93	-0.03	0.05	-0.02	140	-0.02	0.05	-0.02
		500	77	-0.04	0.07	-0.03	143	-0.03	0.07	-0.03
		1000	63	-0.05	0.07	-0.02	143	-0.04	0.06	-0.02
Well-Defined, Moderate Thresholds	50/50	200	465	-0.01	0.02	-0.01	485	-0.01	0.02	-0.01
		500	487	-0.01	0.02	-0.01	500	0.00	0.01	-0.01
		1000	499	-0.01	0.02	-0.01	500	0.00	0.01	-0.01
	60/40	200	500	0.00	0.01	0.00	500	0.00	0.00	0.00
		500	500	0.00	0.00	0.00	500	0.00	0.00	0.00
		1000	500	0.00	0.01	0.00	500	0.00	0.00	0.00
	80/20	200	174	-0.01	0.03	-0.01	218	-0.01	0.02	-0.01
		500	138	-0.01	0.02	-0.01	219	-0.01	0.02	-0.01
		1000	102	-0.01	0.02	-0.01	186	0.00	0.02	-0.01
Well-Defined, High Thresholds	50/50	200	488	0.00	0.00	0.00	497	0.00	0.00	0.00
		500	499	0.00	0.00	0.00	500	0.00	0.00	0.00
		1000	500	0.00	0.00	0.00	500	0.00	0.00	0.00
	60/40	200	500	0.00	0.00	0.00	500	0.00	0.00	0.00
		500	500	0.00	0.00	0.00	500	0.00	0.00	0.00
		1000	500	0.00	0.00	0.00	500	0.00	0.00	0.00
	80/20	200	197	-0.02	0.02	0.00	260	-0.01	0.01	0.00
		500	159	-0.01	0.01	0.00	244	-0.01	0.01	0.00
		1000	123	-0.01	0.01	0.00	247	-0.01	0.01	0.00
Poorly-Defined, Moderate Thresholds	50/50	200	471	-0.01	0.00	0.01	473	-0.01	-0.01	0.02
		500	496	-0.02	-0.01	0.03	499	-0.01	-0.01	0.02
		1000	498	-0.02	-0.01	0.03	500	-0.02	-0.01	0.02
	60/40	200	492	0.00	-0.01	0.01	496	0.00	-0.01	0.01
		500	500	-0.01	-0.01	0.01	498	0.00	0.00	0.01
		1000	500	-0.01	-0.01	0.01	499	0.00	0.00	0.01
	80/20	200	203	0.00	-0.01	0.01	253	0.00	-0.01	0.01
		500	214	-0.02	-0.01	0.03	305	-0.02	-0.01	0.03
		1000	221	-0.04	0.00	0.04	353	-0.03	0.00	0.04
Poorly-Defined High Thresholds	50/50	200	0	--	--	--	0	--	--	--
		500	0	--	--	--	0	--	--	--
		1000	0	--	--	--	0	--	--	--
	60/40	200	48	0.00	0.06	-0.06	267	0.00	0.02	-0.02
		500	2	0.01	0.04	-0.05	167	0.00	0.01	-0.01
		1000	0	--	--	--	116	0.00	0.01	-0.01
	80/20	200	0	--	--	--	0	--	--	--
		500	0	--	--	--	0	--	--	--
		1000	0	--	--	--	0	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Class 3 serves as the reference class in all models.

Table A.13b. Latent Class Prevalence Parameter Recovery: LMI Pattern B, Three-Class Solutions

Absolute Bias in Estimated Class Prevalence Parameters										
Ordered Transition Pattern							Unordered Transition Pattern			
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	C1#1	C1#2	C1#3	Number Valid Reps	C1#1	C1#2	C1#3
Well-Defined, Low Thresholds	50/50	200	370	0.10	-0.01	-0.09	350	0.10	-0.01	-0.08
		500	431	0.10	-0.01	-0.09	385	0.10	-0.01	-0.09
		1000	461	0.10	-0.01	-0.09	436	0.10	-0.01	-0.09
	60/40	200	428	0.07	-0.01	-0.06	400	0.07	-0.01	-0.06
		500	464	0.08	-0.01	-0.06	451	0.08	-0.01	-0.06
		1000	483	0.08	-0.01	-0.07	472	0.08	-0.01	-0.07
	80/20	200	468	0.03	0.00	-0.03	459	0.04	-0.01	-0.03
		500	491	0.04	-0.01	-0.02	490	0.04	-0.02	-0.02
		1000	477	0.04	-0.01	-0.02	484	0.04	-0.01	-0.03
Well-Defined, Moderate Thresholds	50/50	200	491	0.10	0.00	-0.10	473	0.10	0.00	-0.10
		500	499	0.11	0.00	-0.10	495	0.11	0.00	-0.11
		1000	500	0.11	0.00	-0.11	500	0.11	0.00	-0.11
	60/40	200	497	0.07	0.00	-0.07	489	0.07	0.00	-0.07
		500	500	0.07	0.00	-0.07	500	0.08	0.00	-0.08
		1000	500	0.08	0.00	-0.08	500	0.08	0.00	-0.08
	80/20	200	500	0.03	0.00	-0.03	500	0.03	0.00	-0.03
		500	500	0.03	0.00	-0.03	500	0.03	0.00	-0.03
		1000	500	0.03	0.00	-0.03	500	0.03	0.00	-0.03
Well-Defined, High Thresholds	50/50	200	497	0.13	0.00	-0.13	491	0.13	0.00	-0.13
		500	500	0.15	0.00	-0.15	500	0.14	0.00	-0.14
		1000	500	0.15	0.00	-0.15	500	0.15	0.00	-0.15
	60/40	200	500	0.10	0.00	-0.10	499	0.10	0.00	-0.10
		500	500	0.11	0.00	-0.11	500	0.11	0.00	-0.11
		1000	500	0.12	0.00	-0.12	500	0.12	0.00	-0.12
	80/20	200	500	0.04	0.00	-0.04	500	0.04	0.00	-0.04
		500	500	0.05	0.00	-0.05	500	0.05	0.00	-0.05
		1000	500	0.05	0.00	-0.05	500	0.05	0.00	-0.05
Poorly-Defined, Moderate Thresholds	50/50	200	485	0.05	0.00	-0.05	473	0.05	-0.01	-0.04
		500	499	0.05	-0.01	-0.04	498	0.04	-0.01	-0.04
		1000	500	0.05	-0.01	-0.04	500	0.05	-0.01	-0.04
	60/40	200	491	0.04	0.00	-0.04	476	0.04	-0.01	-0.03
		500	499	0.04	0.00	-0.03	499	0.04	0.00	-0.03
		1000	500	0.04	0.00	-0.03	498	0.04	0.00	-0.03
	80/20	200	497	0.02	-0.01	-0.01	490	0.02	-0.01	-0.01
		500	499	0.02	0.00	-0.01	500	0.02	0.00	-0.01
		1000	500	0.02	0.00	-0.02	499	0.02	0.00	-0.02
Poorly-Defined High Thresholds	50/50	200	0	--	--	--	0	--	--	--
		500	0	--	--	--	0	--	--	--
		1000	0	--	--	--	0	--	--	--
	60/40	200	4	0.09	0.07	-0.16	3	0.08	0.08	-0.16
		500	0	--	--	--	0	--	--	--
		1000	0	--	--	--	0	--	--	--
	80/20	200	161	0.04	0.02	-0.05	137	0.04	0.02	-0.05
		500	60	0.04	0.01	-0.04	42	0.04	0.01	-0.05
		1000	18	0.04	0.02	-0.06	10	0.04	0.00	-0.04

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Class 3 serves as the reference class in all models.

Table A.14a. Latent Class Prevalence Parameter Recovery: LMI Pattern A, Four-Class Solutions

Absolute Bias in Estimated Class Prevalence Parameters												
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern				Number Valid Reps	Unordered Transition Pattern			
				C1#1	C1#2	C1#3	C1#4		C1#1	C1#2	C1#3	C1#4
Well-Defined, Low Thresholds	50/50	200	368	-0.05	0.01	-0.04	--	313	-0.04	0.00	-0.04	--
		500	468	-0.02	0.01	-0.02	--	439	-0.03	0.01	-0.03	--
		1000	474	-0.01	0.01	-0.01	--	483	-0.02	0.01	-0.02	--
	60/40	200	185	-0.05	0.00	-0.03	--	115	-0.05	-0.01	-0.03	--
		500	283	-0.04	0.01	-0.03	--	137	-0.04	0.01	-0.02	--
		1000	387	-0.02	0.01	-0.02	--	233	-0.03	0.01	-0.02	--
	80/20	200	434	-0.04	-0.01	0.00	--	432	-0.04	-0.01	-0.01	--
		500	468	-0.02	0.00	-0.01	--	468	-0.02	0.01	-0.01	--
		1000	473	-0.01	0.00	0.00	--	477	-0.01	0.01	-0.01	--
Well-Defined, Moderate Thresholds	50/50	200	410	-0.01	0.00	0.00	--	423	-0.01	0.00	-0.01	--
		500	458	0.00	0.00	0.00	--	470	0.00	0.00	0.00	--
		1000	478	0.00	0.00	0.00	--	492	0.00	0.00	0.00	--
	60/40	200	415	-0.01	0.00	0.00	--	365	-0.02	0.00	-0.01	--
		500	446	0.00	0.00	0.00	--	475	0.00	0.00	0.00	--
		1000	470	0.00	0.00	0.00	--	488	0.00	0.00	0.00	--
	80/20	200	388	-0.01	0.00	0.00	--	402	-0.01	0.00	0.00	--
		500	441	0.00	0.00	0.00	--	467	0.00	0.00	0.00	--
		1000	474	0.00	0.00	0.00	--	479	0.00	0.00	0.00	--
Well-Defined, High Thresholds	50/50	200	289	0.00	0.00	0.00	--	313	0.00	0.00	0.00	--
		500	403	0.00	0.00	0.00	--	432	0.00	0.00	0.00	--
		1000	441	0.00	0.00	0.00	--	476	0.00	0.00	0.00	--
	60/40	200	290	0.00	0.00	0.00	--	345	0.00	0.00	0.00	--
		500	398	0.00	0.00	0.00	--	430	0.00	0.00	0.00	--
		1000	451	0.00	0.00	0.00	--	479	0.00	0.00	0.00	--
	80/20	200	324	0.00	0.00	0.00	--	312	0.00	0.00	0.00	--
		500	389	0.00	0.00	0.00	--	413	0.00	0.00	0.00	--
		1000	419	0.00	0.00	0.00	--	447	0.00	0.00	0.00	--
Poorly-Defined, Moderate Thresholds	50/50	200	271	-0.03	-0.01	-0.06	--	242	-0.03	-0.03	-0.04	--
		500	421	-0.01	-0.01	-0.02	--	357	-0.01	-0.01	-0.03	--
		1000	480	-0.01	-0.01	-0.02	--	457	-0.01	-0.01	-0.02	--
	60/40	200	121	-0.03	-0.02	-0.04	--	106	-0.02	-0.02	-0.06	--
		500	171	-0.02	-0.01	-0.03	--	95	-0.02	-0.01	-0.03	--
		1000	275	-0.01	-0.01	-0.02	--	156	-0.02	-0.01	-0.02	--
	80/20	200	440	-0.02	-0.02	-0.02	--	442	-0.02	-0.02	-0.03	--
		500	480	-0.01	-0.01	-0.01	--	489	-0.01	-0.01	-0.02	--
		1000	484	-0.01	0.00	-0.01	--	486	-0.01	0.00	-0.01	--
Poorly-Defined High Thresholds	50/50	200	298	0.00	0.01	-0.01	--	299	0.00	0.02	-0.02	--
		500	386	0.00	0.00	0.00	--	397	0.00	0.01	0.00	--
		1000	428	0.00	0.00	0.00	--	454	0.00	0.00	0.00	--
	60/40	200	301	0.00	0.02	-0.02	--	311	0.00	0.02	-0.02	--
		500	352	0.00	0.00	0.00	--	388	0.00	0.01	0.00	--
		1000	429	0.00	0.00	0.00	--	445	0.00	0.00	0.00	--
	80/20	200	330	0.00	0.01	-0.01	--	331	-0.01	0.01	-0.01	--
		500	411	0.00	0.00	0.00	--	413	0.00	0.00	0.00	--
		1000	432	0.00	0.00	0.00	--	456	0.00	0.00	0.00	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Class 4 serves as the reference class in all models.

Table A.14b. Latent Class Prevalence Parameter Recovery: LMI Pattern B, Four-Class Solutions

Absolute Bias in Estimated Class Prevalence Parameters												
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern				Number Valid Reps	Unordered Transition Pattern			
				C1#1	C1#2	C1#3	C1#4		C1#1	C1#2	C1#3	C1#4
Well-Defined, Low Thresholds	50/50	200	348	-0.03	-0.01	0.01	0.04	364	-0.03	-0.02	0.01	0.04
		500	451	-0.02	0.00	-0.01	0.02	474	-0.01	-0.01	0.00	0.02
		1000	469	-0.01	0.00	0.00	0.02	492	-0.01	0.00	0.00	0.01
	60/40	200	303	-0.03	-0.02	0.00	0.05	319	-0.03	-0.02	0.00	0.06
		500	427	-0.02	0.00	-0.01	0.03	457	-0.01	-0.01	-0.01	0.03
		1000	470	-0.01	0.00	-0.01	0.02	488	-0.01	0.00	-0.01	0.02
	80/20	200	155	-0.05	-0.01	-0.01	0.07	159	-0.05	-0.01	-0.02	0.07
		500	236	-0.03	0.00	-0.01	0.04	238	-0.03	0.00	-0.01	0.05
		1000	372	-0.02	0.00	-0.01	0.03	366	-0.02	0.00	-0.02	0.03
Well-Defined, Moderate Thresholds	50/50	200	489	-0.01	0.00	0.00	0.00	495	0.00	0.00	0.00	0.00
		500	482	0.00	0.00	0.00	0.00	494	0.00	0.00	0.00	0.00
		1000	484	0.00	0.00	0.00	0.00	498	0.00	0.00	0.00	0.00
	60/40	200	487	-0.01	0.00	0.00	0.01	492	-0.01	0.00	0.00	0.01
		500	480	0.00	0.00	0.00	0.00	496	0.00	0.00	0.00	0.00
		1000	478	0.00	0.00	0.00	0.00	500	0.00	0.00	0.00	0.00
	80/20	200	459	-0.01	0.00	0.00	0.01	456	-0.01	0.00	0.00	0.01
		500	485	0.00	0.00	0.00	0.00	494	0.00	0.00	0.00	0.00
		1000	492	0.00	0.00	0.00	0.00	495	0.00	0.00	0.00	0.00
Well-Defined, High Thresholds	50/50	200	445	0.00	0.00	0.00	0.00	486	0.00	0.00	0.00	0.00
		500	499	0.00	0.00	0.00	0.00	500	0.00	0.00	0.00	0.00
		1000	498	0.00	0.00	0.00	0.00	500	0.00	0.00	0.00	0.00
	60/40	200	432	0.00	0.00	0.00	0.00	471	0.00	0.00	0.00	0.00
		500	499	0.00	0.00	0.00	0.00	499	0.00	0.00	0.00	0.00
		1000	498	0.00	0.00	0.00	0.00	500	0.00	0.00	0.00	0.00
	80/20	200	379	0.00	0.00	0.00	0.00	424	0.00	0.00	0.00	0.00
		500	494	0.00	0.00	0.00	0.00	495	0.00	0.00	0.00	0.00
		1000	498	0.00	0.00	0.00	0.00	500	0.00	0.00	0.00	0.00
Poorly-Defined, Moderate Thresholds	50/50	200	266	-0.02	-0.01	-0.02	0.05	270	-0.02	-0.02	-0.01	0.05
		500	401	-0.01	-0.01	-0.01	0.03	425	-0.01	-0.01	-0.01	0.03
		1000	454	-0.01	-0.01	-0.01	0.02	476	-0.01	-0.01	-0.01	0.02
	60/40	200	201	-0.02	-0.02	-0.02	0.06	207	-0.03	-0.03	-0.01	0.07
		500	329	-0.01	-0.01	-0.01	0.04	335	-0.01	-0.02	-0.02	0.05
		1000	440	-0.01	-0.01	-0.01	0.02	451	-0.01	-0.01	-0.01	0.03
	80/20	200	118	-0.02	-0.02	-0.02	0.07	131	-0.04	-0.03	-0.02	0.09
		500	136	-0.02	-0.02	-0.02	0.05	132	-0.02	-0.02	-0.02	0.06
		1000	208	-0.01	-0.01	-0.01	0.03	205	-0.01	-0.01	-0.02	0.04
Poorly-Defined High Thresholds	50/50	200	485	-0.01	0.02	-0.02	0.01	486	-0.01	0.01	-0.02	0.01
		500	498	0.00	0.01	-0.01	0.01	498	0.00	0.01	-0.01	0.01
		1000	499	0.00	0.01	-0.01	0.00	497	0.00	0.01	-0.01	0.00
	60/40	200	486	-0.01	0.02	-0.02	0.01	485	-0.01	0.02	-0.02	0.01
		500	496	0.00	0.02	-0.02	0.01	497	0.00	0.01	-0.02	0.01
		1000	498	0.00	0.01	-0.01	0.00	498	0.00	0.01	-0.01	0.00
	80/20	200	463	-0.01	0.02	-0.03	0.01	472	-0.01	0.02	-0.02	0.01
		500	496	0.00	0.02	-0.02	0.01	495	0.00	0.02	-0.02	0.01
		1000	498	0.00	0.02	-0.02	0.00	498	0.00	0.02	-0.02	0.00

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Class 4 serves as the reference class in all models.

Table A.15a. Transition Probability Parameter Recovery: LMI Pattern A, Ordered Transition Matrix, Three-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Ordered Transition Pattern								
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3
Well-Defined, Low Thresholds	50/50	200	0.00	0.01	-0.01	0.09	-0.14	0.05	0.21	0.04	-0.25
		500	0.01	0.02	-0.03	0.08	-0.13	0.05	0.21	0.01	-0.22
		1000	0.01	0.03	-0.04	0.09	-0.14	0.05	0.21	0.00	-0.21
	60/40	200	-0.01	0.00	0.00	0.07	-0.12	0.05	0.07	0.06	-0.13
		500	0.01	0.00	-0.01	0.05	-0.09	0.03	0.07	0.03	-0.10
		1000	0.02	0.01	-0.02	0.05	-0.08	0.03	0.07	0.02	-0.08
	80/20	200	0.02	0.00	-0.02	0.12	-0.14	0.02	0.77	0.01	-0.78
		500	0.02	0.02	-0.04	0.10	-0.12	0.02	0.79	0.00	-0.80
		1000	0.02	0.02	-0.04	0.10	-0.12	0.02	0.82	0.00	-0.82
Well-Defined, Moderate Thresholds	50/50	200	0.01	0.00	-0.01	0.02	-0.03	0.00	0.24	0.01	-0.24
		500	0.01	0.01	-0.02	0.02	-0.03	0.01	0.23	0.00	-0.23
		1000	0.01	0.01	-0.02	0.02	-0.03	0.01	0.23	0.00	-0.23
	60/40	200	0.01	0.00	-0.01	0.02	-0.01	0.00	0.06	0.01	-0.07
		500	0.01	0.00	-0.01	0.01	-0.01	0.00	0.06	0.01	-0.06
		1000	0.01	0.00	-0.01	0.01	-0.01	0.00	0.05	0.00	-0.06
	80/20	200	0.02	0.00	-0.02	0.03	-0.01	-0.02	0.93	0.00	-0.94
		500	0.01	0.01	-0.02	0.03	-0.02	-0.02	0.97	0.00	-0.97
		1000	0.02	0.00	-0.02	0.03	-0.02	-0.01	0.98	0.00	-0.98
Well-Defined, High Thresholds	50/50	200	0.01	0.00	-0.01	0.02	0.00	-0.02	0.37	0.00	-0.37
		500	0.01	0.00	-0.01	0.02	0.00	-0.01	0.40	0.00	-0.40
		1000	0.01	0.00	-0.01	0.02	0.00	-0.02	0.43	0.00	-0.43
	60/40	200	0.01	0.00	-0.01	0.01	0.00	-0.01	0.10	0.00	-0.10
		500	0.01	0.00	-0.01	0.01	0.00	-0.01	0.10	0.00	-0.11
		1000	0.01	0.00	-0.01	0.01	0.00	-0.01	0.11	0.00	-0.11
	80/20	200	0.01	0.00	-0.01	0.02	0.01	-0.02	0.98	0.00	-0.98
		500	0.01	0.00	-0.01	0.02	0.00	-0.02	1.00	0.00	-1.00
		1000	0.01	0.00	-0.01	0.02	0.00	-0.02	1.00	0.00	-1.00
Poorly-Defined, Moderate Thresholds	50/50	200	0.01	-0.01	0.00	0.03	-0.04	0.01	0.13	0.06	-0.19
		500	0.02	-0.01	-0.01	0.02	-0.02	0.00	0.11	0.03	-0.14
		1000	0.02	0.00	-0.02	0.01	0.00	-0.01	0.11	0.02	-0.12
	60/40	200	0.00	-0.01	0.02	0.03	-0.04	0.01	0.06	0.05	-0.11
		500	0.01	-0.01	0.00	0.02	-0.01	-0.01	0.05	0.03	-0.08
		1000	0.01	0.00	-0.01	0.01	0.00	-0.01	0.04	0.02	-0.06
	80/20	200	0.02	-0.02	-0.01	0.04	-0.03	-0.01	0.34	0.06	-0.40
		500	0.03	0.00	-0.03	0.02	-0.04	0.02	0.28	0.02	-0.30
		1000	0.03	0.01	-0.04	0.01	-0.04	0.03	0.23	0.01	-0.24
Poorly-Defined High Thresholds	50/50	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	60/40	200	0.00	0.02	-0.03	0.00	0.01	-0.02	0.03	0.08	-0.11
		500	0.00	0.01	-0.01	0.00	0.08	-0.08	0.07	0.00	-0.07
		1000	--	--	--	--	--	--	--	--	--
	80/20	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table A.15b. Transition Probability Parameter Recovery: LMI Pattern A, Unordered Transition Matrix, Three-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Unordered Transition Pattern								
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3
Well-Defined, Low Thresholds	50/50	200	0.00	0.01	-0.01	0.08	-0.13	0.05	0.18	0.02	-0.20
		500	0.01	0.02	-0.03	0.08	-0.11	0.03	0.19	-0.02	-0.18
		1000	0.01	0.02	-0.04	0.08	-0.11	0.03	0.20	-0.03	-0.17
	60/40	200	-0.01	0.00	0.01	0.06	-0.10	0.04	0.04	0.06	-0.10
		500	0.01	-0.01	-0.01	0.04	-0.06	0.02	0.04	0.02	-0.06
		1000	0.02	0.00	-0.02	0.04	-0.04	0.01	0.04	0.00	-0.04
	80/20	200	0.01	0.00	-0.02	0.10	-0.12	0.02	0.71	-0.02	-0.69
		500	0.02	0.02	-0.04	0.11	-0.11	0.01	0.73	-0.04	-0.69
		1000	0.01	0.03	-0.04	0.09	-0.10	0.02	0.78	-0.04	-0.74
Well-Defined, Moderate Thresholds	50/50	200	0.01	0.00	-0.01	0.02	-0.02	-0.01	0.22	0.00	-0.21
		500	0.01	0.00	-0.02	0.03	-0.02	0.00	0.23	-0.01	-0.22
		1000	0.01	0.01	-0.02	0.03	-0.02	-0.01	0.25	-0.01	-0.24
	60/40	200	0.01	0.00	-0.01	0.02	-0.01	-0.01	0.04	0.00	-0.04
		500	0.01	0.00	-0.01	0.02	-0.01	-0.01	0.04	0.00	-0.04
		1000	0.01	0.00	-0.01	0.02	-0.01	-0.01	0.04	0.00	-0.04
	80/20	200	0.01	0.00	-0.02	0.02	-0.01	-0.02	0.88	-0.01	-0.86
		500	0.01	0.01	-0.02	0.03	-0.02	-0.01	0.89	-0.02	-0.88
		1000	0.02	0.00	-0.02	0.03	-0.02	-0.01	0.91	-0.02	-0.89
Well-Defined, High Thresholds	50/50	200	0.01	0.00	-0.01	0.02	0.00	-0.02	0.33	0.00	-0.33
		500	0.01	0.00	-0.01	0.02	0.00	-0.02	0.36	0.00	-0.36
		1000	0.01	0.00	-0.01	0.02	0.00	-0.02	0.37	0.00	-0.37
	60/40	200	0.01	0.00	-0.01	0.02	0.00	-0.02	0.07	0.00	-0.07
		500	0.01	0.00	-0.01	0.02	0.00	-0.02	0.08	0.00	-0.08
		1000	0.01	0.00	-0.01	0.02	0.00	-0.02	0.08	0.00	-0.08
	80/20	200	0.01	0.00	-0.01	0.02	0.01	-0.02	0.90	0.00	-0.90
		500	0.01	0.00	-0.01	0.02	0.00	-0.02	0.91	0.00	-0.91
		1000	0.01	0.00	-0.01	0.02	0.00	-0.02	0.91	0.00	-0.91
Poorly-Defined, Moderate Thresholds	50/50	200	0.00	-0.01	0.01	0.03	-0.04	0.01	0.12	0.04	-0.16
		500	0.02	-0.01	-0.01	0.01	-0.01	-0.01	0.10	0.02	-0.12
		1000	0.02	0.00	-0.02	0.01	0.01	-0.01	0.10	0.00	-0.11
	60/40	200	0.00	-0.01	0.02	0.03	-0.04	0.01	0.04	0.03	-0.07
		500	0.01	-0.01	0.00	0.02	-0.01	-0.01	0.03	0.02	-0.04
		1000	0.01	0.00	0.00	0.01	0.00	-0.01	0.03	0.01	-0.03
	80/20	200	0.01	-0.01	0.00	0.04	-0.04	0.00	0.35	0.05	-0.40
		500	0.03	0.00	-0.02	0.01	-0.02	0.01	0.27	0.00	-0.27
		1000	0.03	0.00	-0.03	0.00	-0.03	0.02	0.23	-0.02	-0.21
Poorly-Defined High Thresholds	50/50	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	60/40	200	0.01	0.00	-0.01	0.01	0.00	-0.01	0.05	0.04	-0.09
		500	0.02	0.00	-0.02	0.01	0.03	-0.04	0.07	-0.02	-0.06
		1000	0.01	0.01	-0.02	0.01	0.03	-0.04	0.08	-0.03	-0.05
	80/20	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table A.15c. Transition Probability Parameter Recovery: LMI Pattern B, Ordered Transition Matrix, Three-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Ordered Transition Pattern								
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3
Well-Defined, Low Thresholds	50/50	200	-0.25	0.04	0.20	0.05	-0.03	-0.01	0.01	0.12	-0.13
		500	-0.24	0.05	0.19	0.03	0.02	-0.05	0.00	0.10	-0.10
		1000	-0.24	0.05	0.19	0.02	0.04	-0.06	0.00	0.07	-0.07
	60/40	200	-0.20	0.04	0.16	0.04	-0.04	0.00	0.01	0.11	-0.12
		500	-0.19	0.04	0.15	0.03	0.01	-0.04	0.00	0.08	-0.09
		1000	-0.19	0.04	0.15	0.02	0.03	-0.05	0.00	0.06	-0.06
	80/20	200	-0.12	0.02	0.09	0.04	-0.06	0.02	0.02	0.09	-0.11
		500	-0.10	0.02	0.08	0.03	-0.01	-0.01	0.01	0.06	-0.06
		1000	-0.10	0.02	0.08	0.02	0.01	-0.02	0.00	0.04	-0.04
Well-Defined, Moderate Thresholds	50/50	200	-0.20	-0.01	0.21	0.00	0.01	-0.02	0.00	0.02	-0.02
		500	-0.21	-0.02	0.22	0.00	0.01	-0.02	0.00	0.01	-0.01
		1000	-0.22	-0.02	0.24	0.00	0.01	-0.02	0.00	0.01	-0.01
	60/40	200	-0.15	-0.01	0.16	0.00	0.01	-0.01	0.00	0.02	-0.02
		500	-0.16	-0.01	0.17	0.00	0.01	-0.01	0.00	0.01	-0.01
		1000	-0.17	-0.01	0.18	0.00	0.01	-0.02	0.00	0.01	-0.01
	80/20	200	-0.07	0.00	0.07	0.00	0.00	-0.01	0.00	0.02	-0.02
		500	-0.07	0.00	0.07	0.00	0.00	-0.01	0.00	0.01	-0.01
		1000	-0.07	0.00	0.07	0.00	0.01	-0.01	0.00	0.01	-0.01
Well-Defined, High Thresholds	50/50	200	-0.24	-0.04	0.27	0.00	0.00	0.00	0.00	0.01	-0.01
		500	-0.26	-0.04	0.30	0.00	0.00	0.00	0.00	0.00	0.00
		1000	-0.27	-0.04	0.31	0.00	0.00	0.00	0.00	0.00	0.00
	60/40	200	-0.19	-0.03	0.22	0.00	0.00	0.00	0.00	0.00	-0.01
		500	-0.21	-0.03	0.25	0.00	0.00	0.00	0.00	0.00	0.00
		1000	-0.22	-0.03	0.26	0.00	0.00	0.00	0.00	0.00	0.00
	80/20	200	-0.09	-0.02	0.11	0.00	0.00	0.00	0.00	0.00	0.00
		500	-0.10	-0.02	0.12	0.00	0.00	0.00	0.00	0.00	0.00
		1000	-0.11	-0.02	0.13	0.00	0.00	0.00	0.00	0.00	0.00
Poorly-Defined, Moderate Thresholds	50/50	200	-0.13	-0.02	0.15	0.02	-0.06	0.04	0.02	0.05	-0.07
		500	-0.13	-0.02	0.15	0.01	-0.03	0.02	0.01	0.02	-0.03
		1000	-0.13	-0.02	0.15	0.01	-0.02	0.01	0.00	0.01	-0.01
	60/40	200	-0.11	-0.02	0.12	0.02	-0.06	0.04	0.02	0.05	-0.06
		500	-0.10	-0.02	0.12	0.01	-0.03	0.02	0.01	0.02	-0.03
		1000	-0.10	-0.02	0.12	0.01	-0.02	0.01	0.00	0.01	-0.01
	80/20	200	-0.06	-0.01	0.08	0.02	-0.06	0.03	0.02	0.04	-0.06
		500	-0.06	-0.01	0.07	0.01	-0.03	0.02	0.01	0.02	-0.03
		1000	-0.06	-0.01	0.07	0.01	-0.02	0.01	0.01	0.01	-0.02
Poorly-Defined High Thresholds	50/50	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	60/40	200	-0.21	0.00	0.22	0.00	0.02	-0.02	0.00	0.03	-0.03
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	80/20	200	-0.10	-0.01	0.10	0.00	-0.01	0.01	0.00	0.04	-0.04
		500	-0.12	-0.01	0.13	0.00	0.02	-0.02	0.00	0.01	-0.01
		1000	-0.11	0.00	0.12	0.00	0.02	-0.02	0.00	0.01	-0.01

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table A.15d. Transition Probability Parameter Recovery: LMI Pattern B, Unordered Transition Matrix, Three-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Ordered Transition Pattern								
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3
Well-Defined, Low Thresholds	50/50	200	-0.22	0.04	0.19	0.02	0.00	-0.01	-0.01	0.11	-0.09
		500	-0.22	0.04	0.18	0.01	0.04	-0.05	-0.02	0.09	-0.06
		1000	-0.22	0.05	0.17	0.02	0.05	-0.06	-0.03	0.07	-0.04
	60/40	200	-0.18	0.03	0.15	0.01	-0.01	-0.01	-0.01	0.09	-0.09
		500	-0.18	0.03	0.14	0.02	0.03	-0.04	-0.02	0.08	-0.06
		1000	-0.17	0.04	0.14	0.02	0.04	-0.05	-0.03	0.06	-0.03
	80/20	200	-0.10	0.01	0.09	0.02	-0.04	0.02	0.00	0.08	-0.08
		500	-0.08	0.01	0.08	0.01	0.00	-0.02	-0.01	0.05	-0.04
		1000	-0.09	0.01	0.07	0.01	0.02	-0.03	-0.02	0.03	-0.01
Well-Defined, Moderate Thresholds	50/50	200	-0.19	-0.01	0.19	0.00	0.02	-0.02	-0.02	0.01	0.01
		500	-0.20	-0.01	0.21	0.00	0.02	-0.02	-0.02	0.00	0.01
		1000	-0.21	-0.01	0.22	0.00	0.02	-0.02	-0.02	0.00	0.02
	60/40	200	-0.15	0.00	0.15	0.00	0.01	-0.02	-0.01	0.01	0.01
		500	-0.15	-0.01	0.16	0.00	0.01	-0.02	-0.01	0.00	0.01
		1000	-0.16	0.00	0.16	0.00	0.01	-0.02	-0.01	0.00	0.01
	80/20	200	-0.07	0.00	0.07	0.00	0.01	-0.01	-0.01	0.01	0.00
		500	-0.07	0.00	0.07	0.00	0.01	-0.01	-0.01	0.00	0.01
		1000	-0.07	0.00	0.07	0.00	0.01	-0.01	-0.01	0.00	0.01
Well-Defined, High Thresholds	50/50	200	-0.23	-0.03	0.26	0.00	0.00	0.00	-0.01	0.00	0.01
		500	-0.24	-0.03	0.28	0.00	0.00	0.00	0.00	0.00	0.01
		1000	-0.26	-0.03	0.29	0.00	0.00	0.00	0.00	0.00	0.01
	60/40	200	-0.18	-0.03	0.21	0.00	0.00	0.00	-0.01	0.00	0.01
		500	-0.20	-0.03	0.23	0.00	0.00	0.00	0.00	0.00	0.01
		1000	-0.22	-0.03	0.24	0.00	0.00	0.00	0.00	0.00	0.00
	80/20	200	-0.09	-0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.01
		500	-0.10	-0.02	0.12	0.00	0.00	0.00	0.00	0.00	0.00
		1000	-0.11	-0.01	0.12	0.00	0.00	0.00	0.00	0.00	0.00
Poorly-Defined, Moderate Thresholds	50/50	200	-0.11	-0.02	0.13	0.00	-0.04	0.05	0.00	0.02	-0.02
		500	-0.11	-0.02	0.13	-0.01	-0.01	0.02	-0.01	-0.01	0.02
		1000	-0.11	-0.02	0.13	-0.01	0.00	0.01	-0.02	-0.02	0.04
	60/40	200	-0.09	-0.02	0.11	0.00	-0.04	0.04	0.01	0.02	-0.03
		500	-0.09	-0.02	0.11	-0.01	-0.01	0.02	-0.01	-0.01	0.01
		1000	-0.09	-0.01	0.10	-0.01	0.00	0.01	-0.01	-0.02	0.03
	80/20	200	-0.05	-0.02	0.07	0.00	-0.04	0.04	0.01	0.02	-0.03
		500	-0.05	-0.01	0.06	-0.01	-0.01	0.02	0.00	0.00	0.00
		1000	-0.05	-0.01	0.06	0.00	0.00	0.01	-0.01	-0.01	0.02
Poorly-Defined High Thresholds	50/50	200	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	60/40	200	-0.20	-0.02	0.23	-0.01	0.05	-0.05	-0.01	-0.02	0.04
		500	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--
	80/20	200	-0.08	-0.01	0.09	0.00	-0.02	0.02	-0.01	0.03	-0.02
		500	-0.10	0.00	0.10	0.00	0.03	-0.03	-0.01	-0.01	0.02
		1000	-0.11	0.00	0.11	0.01	0.01	-0.02	-0.02	0.01	0.01

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table A.16a. Transition Probability Parameter Recovery: LMI Pattern A, Ordered Transition Matrix, Four-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Absolute Bias in Estimated Transition Matrix Parameters															
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#4 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#4 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#4 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4	C2#4 on C1#4
Well-Defined, Low Thresholds	50/50	200	-0.11	0.02	0.01	0.08	0.05	-0.16	0.04	0.06	0.04	0.08	-0.10	-0.02	--	--	--	--
		500	-0.03	-0.01	0.00	0.03	0.03	-0.06	0.00	0.03	0.02	0.03	-0.06	0.01	--	--	--	--
		1000	-0.01	0.00	0.00	0.02	0.02	-0.03	0.00	0.01	0.02	0.02	-0.04	0.00	--	--	--	--
	60/40	200	-0.12	0.01	0.02	0.09	0.06	-0.17	0.06	0.05	0.03	0.09	0.03	-0.15	--	--	--	--
		500	-0.06	-0.01	0.01	0.06	0.03	-0.06	0.01	0.02	0.01	0.04	0.11	-0.16	--	--	--	--
		1000	-0.02	0.00	0.00	0.03	0.02	-0.03	0.00	0.01	0.01	0.02	0.16	-0.19	--	--	--	--
	80/20	200	-0.09	0.01	0.02	0.06	0.06	-0.12	0.02	0.04	0.06	0.04	-0.74	0.65	--	--	--	--
		500	-0.02	-0.01	0.00	0.03	0.03	-0.04	-0.01	0.02	0.03	0.02	-0.78	0.73	--	--	--	--
		1000	-0.01	0.00	0.00	0.02	0.02	-0.03	0.00	0.01	0.02	0.01	-0.79	0.75	--	--	--	--
Well-Defined, Moderate Thresholds	50/50	200	0.00	0.00	0.00	0.01	0.01	-0.01	0.00	0.00	0.01	0.01	-0.02	0.00	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01	0.00	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
	60/40	200	0.00	0.00	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	0.01	0.18	-0.19	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.19	-0.20	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.19	-0.20	--	--	--	--
	80/20	200	0.00	0.00	0.00	0.01	0.01	-0.01	0.00	0.00	0.01	0.01	-0.80	0.78	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.80	0.79	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.79	--	--	--	--
Well-Defined, High Thresholds	50/50	200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
	60/40	200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.20	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.19	-0.20	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.20	--	--	--	--
	80/20	200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.79	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--

Continues...

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Poorly-Defined, Moderate Thresholds	50/50	200	-0.08	-0.02	0.02	0.08	0.02	-0.08	0.00	0.06	0.04	0.06	-0.11	0.01	--	--	--	--
		500	-0.03	-0.02	0.01	0.04	0.01	-0.03	-0.01	0.03	0.02	0.02	-0.07	0.03	--	--	--	--
		1000	-0.02	-0.01	0.00	0.03	0.01	-0.01	-0.01	0.01	0.01	0.02	-0.04	0.01	--	--	--	--
	60/40	200	-0.09	-0.03	0.02	0.10	0.02	-0.10	0.01	0.07	0.03	0.05	0.06	-0.14	--	--	--	--
		500	-0.04	-0.02	0.00	0.06	0.01	-0.03	-0.02	0.03	0.02	0.02	0.11	-0.15	--	--	--	--
		1000	-0.03	-0.01	0.00	0.04	0.01	-0.01	-0.02	0.02	0.01	0.01	0.15	-0.17	--	--	--	--
	80/20	200	-0.06	-0.02	0.01	0.07	0.03	-0.08	0.01	0.04	0.04	0.05	-0.74	0.66	--	--	--	--
		500	-0.02	-0.02	0.00	0.04	0.01	-0.03	-0.01	0.02	0.02	0.02	-0.77	0.73	--	--	--	--
		1000	-0.01	-0.01	0.00	0.02	0.01	-0.02	-0.01	0.01	0.01	0.01	-0.78	0.75	--	--	--	--
Poorly-Defined High Thresholds	50/50	200	0.00	-0.01	0.00	0.01	0.00	-0.04	0.02	0.02	0.00	0.04	-0.05	0.00	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	0.00	0.02	-0.01	0.00	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.01	-0.01	0.00	--	--	--	--
	60/40	200	-0.01	0.00	0.00	0.01	0.00	-0.04	0.03	0.01	0.00	0.06	0.14	-0.20	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	-0.02	0.01	0.00	0.00	0.02	0.18	-0.20	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.01	0.19	-0.20	--	--	--	--
	80/20	200	0.00	-0.01	0.00	0.01	0.00	-0.02	0.00	0.02	0.00	0.00	-0.80	0.79	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.01	0.00	0.00	-0.80	0.79	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	0.00	0.00	-0.80	0.79	--	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates that for the models generated under LMI Pattern A, a fourth class at Time 1 is not generated, so there are no population values to which estimates can be compared.

Table A.16b. Transition Probability Parameter Recovery: LMI Pattern A, Unordered Transition Matrix, Four-Class Solutions

			Absolute Bias in Estimated Transition Matrix Parameters															
Class Separation Level	Class Prevalence Split	Total Sample Size	C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#4 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#4 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#4 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4	C2#4 on C1#4
Well-Defined, Low Thresholds	50/50	200	-0.10	0.01	0.02	0.07	0.05	-0.15	0.04	0.06	0.02	0.05	-0.09	0.02	--	--	--	--
		500	-0.03	-0.01	0.00	0.04	0.02	-0.05	0.00	0.03	0.01	0.02	-0.05	0.02	--	--	--	--
		1000	-0.01	-0.01	0.00	0.02	0.01	-0.02	-0.01	0.01	0.00	0.00	-0.03	0.03	--	--	--	--
	60/40	200	-0.12	0.01	0.03	0.08	0.04	-0.17	0.07	0.06	0.01	0.07	0.04	-0.12	--	--	--	--
		500	-0.05	-0.01	0.01	0.06	0.02	-0.04	0.00	0.02	0.00	0.02	0.12	-0.14	--	--	--	--
		1000	-0.04	-0.01	-0.01	0.05	0.01	-0.01	-0.01	0.01	-0.01	0.01	0.17	-0.16	--	--	--	--
	80/20	200	-0.08	0.01	0.02	0.06	0.05	-0.13	0.03	0.04	0.04	0.01	-0.74	0.69	--	--	--	--
		500	-0.02	-0.01	0.00	0.03	0.02	-0.03	-0.01	0.02	0.01	0.00	-0.77	0.77	--	--	--	--
		1000	-0.01	-0.01	0.00	0.02	0.01	-0.01	-0.01	0.02	0.00	-0.01	-0.78	0.79	--	--	--	--
Well-Defined, Moderate Thresholds	50/50	200	0.00	0.00	0.00	0.01	0.01	-0.01	0.00	0.00	0.00	0.01	-0.01	0.01	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
	60/40	200	-0.01	-0.01	0.00	0.02	0.00	-0.01	0.00	0.01	-0.01	0.01	0.17	-0.17	--	--	--	--
		500	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.19	-0.19	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.20	--	--	--	--
	80/20	200	0.00	0.00	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	-0.79	0.79	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
Well-Defined, High Thresholds	50/50	200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--	--	--	--
	60/40	200	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.19	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.20	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	-0.20	--	--	--	--
	80/20	200	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.80	0.80	--	--	--	--
Continues...																		

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Poorly-Defined, Moderate Thresholds	50/50	200	-0.08	-0.02	0.02	0.09	0.02	-0.09	0.01	0.06	0.03	0.03	-0.10	0.04	--	--	--	--
		500	-0.03	-0.02	0.00	0.05	0.01	-0.03	-0.01	0.03	0.00	0.01	-0.08	0.08	--	--	--	--
		1000	-0.02	-0.01	0.00	0.03	0.00	-0.01	-0.01	0.02	0.00	0.00	-0.05	0.05	--	--	--	--
	60/40	200	-0.08	-0.03	0.02	0.09	0.02	-0.10	0.01	0.08	0.01	0.04	0.05	-0.11	--	--	--	--
		500	-0.04	-0.02	0.00	0.06	0.00	-0.02	-0.01	0.03	0.01	0.01	0.12	-0.14	--	--	--	--
		1000	-0.03	-0.01	0.00	0.04	0.00	-0.01	-0.01	0.02	0.00	-0.01	0.16	-0.15	--	--	--	--
	80/20	200	-0.07	-0.02	0.01	0.07	0.02	-0.08	0.01	0.05	0.02	0.02	-0.74	0.69	--	--	--	--
		500	-0.02	-0.01	0.00	0.04	0.01	-0.02	-0.01	0.02	0.00	0.00	-0.77	0.77	--	--	--	--
		1000	-0.01	-0.01	0.00	0.02	0.00	-0.01	-0.01	0.01	0.00	-0.01	-0.78	0.78	--	--	--	--
Poorly-Defined High Thresholds	50/50	200	0.00	-0.01	0.00	0.01	0.00	-0.03	0.01	0.02	-0.01	0.03	-0.05	0.02	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	-0.01	0.01	-0.01	0.01	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	--	--	--	--
	60/40	200	-0.01	0.00	0.00	0.01	0.00	-0.05	0.03	0.02	-0.01	0.06	0.14	-0.18	--	--	--	--
		500	0.00	0.00	0.00	0.01	0.00	-0.01	0.01	0.01	-0.01	0.01	0.19	-0.19	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.20	-0.19	--	--	--	--
	80/20	200	-0.01	0.00	0.00	0.01	0.00	-0.02	-0.01	0.02	-0.01	0.00	-0.79	0.81	--	--	--	--
		500	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	-0.01	0.00	-0.80	0.81	--	--	--	--
		1000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	-0.80	0.80	--	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates that for the models generated under LMI Pattern A, a fourth class at Time 1 is not generated, and there are no population values to which estimates can be compared

Table A.16c. Transition Probability Parameter Recovery: LMI Pattern B, Ordered Transition Matrix, Four-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Absolute Bias in Estimated Transition Matrix Parameters															
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#4 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#4 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#4 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4	C2#4 on C1#4
Well-Defined, Low Thresholds	50/50	200	-0.13	0.00	0.04	--	0.05	-0.12	0.05	--	0.03	0.15	-0.26	--	0.09	0.10	-0.28	--
		500	-0.05	-0.01	0.02	--	0.02	-0.04	0.01	--	0.02	0.08	-0.13	--	0.05	0.07	-0.16	--
		1000	-0.02	-0.01	0.01	--	0.01	-0.02	0.00	--	0.01	0.04	-0.07	--	0.03	0.04	-0.10	--
	60/40	200	-0.13	0.00	0.04	--	0.05	-0.13	0.05	--	0.03	0.14	-0.25	--	0.10	0.12	-0.34	--
		500	-0.06	-0.01	0.02	--	0.02	-0.04	0.00	--	0.01	0.07	-0.12	--	0.06	0.09	-0.21	--
		1000	-0.02	-0.01	0.01	--	0.01	-0.02	0.00	--	0.01	0.04	-0.06	--	0.04	0.05	-0.12	--
	80/20	200	-0.12	0.00	0.03	--	0.06	-0.16	0.06	--	0.02	0.11	-0.22	--	0.14	0.16	-0.48	--
		500	-0.05	-0.03	0.01	--	0.02	-0.04	0.00	--	0.01	0.05	-0.10	--	0.11	0.12	-0.34	--
		1000	-0.03	-0.01	0.01	--	0.01	-0.02	-0.01	--	0.01	0.03	-0.05	--	0.09	0.08	-0.24	--
Well-Defined, Moderate Thresholds	50/50	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	0.00	0.02	-0.03	--	0.01	0.02	-0.04	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.02	--	0.01	0.01	-0.02	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.01	0.01	-0.02	--
	60/40	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	0.00	0.02	-0.03	--	0.02	0.02	-0.05	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.02	--	0.01	0.01	-0.03	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.01	0.01	-0.02	--
	80/20	200	0.00	-0.01	0.00	--	0.00	-0.01	0.00	--	0.00	0.02	-0.03	--	0.04	0.04	-0.11	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.02	0.02	-0.05	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.02	0.01	-0.03	--
Well-Defined, High Thresholds	50/50	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.00	0.00	-0.01	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.00	0.00	-0.01	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--
	60/40	200	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.01	--	0.00	0.00	-0.01	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	-0.01	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	-0.01	--
	80/20	200	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	-0.01	--	0.01	0.01	-0.03	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.01	0.00	-0.01	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.01	0.00	-0.01	--

Continues...

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Poorly-Defined, Moderate Thresholds	50/50	200	-0.10	-0.02	0.04	--	0.02	-0.09	0.02	--	0.06	0.10	-0.29	--	0.07	0.09	-0.33	--
		500	-0.04	-0.02	0.02	--	0.01	-0.03	0.00	--	0.02	0.04	-0.14	--	0.03	0.05	-0.16	--
		1000	-0.03	-0.01	0.01	--	0.01	-0.02	-0.01	--	0.01	0.03	-0.08	--	0.02	0.03	-0.10	--
	60/40	200	-0.09	-0.02	0.03	--	0.02	-0.09	0.01	--	0.05	0.09	-0.24	--	0.10	0.09	-0.36	--
		500	-0.04	-0.02	0.02	--	0.01	-0.03	-0.01	--	0.02	0.03	-0.14	--	0.04	0.06	-0.19	--
		1000	-0.03	-0.01	0.01	--	0.01	-0.02	-0.01	--	0.01	0.02	-0.08	--	0.03	0.04	-0.13	--
	80/20	200	-0.10	-0.03	0.04	--	0.02	-0.10	0.02	--	0.03	0.06	-0.21	--	0.16	0.13	-0.48	--
		500	-0.04	-0.03	0.01	--	0.01	-0.03	-0.02	--	0.02	0.03	-0.12	--	0.09	0.10	-0.33	--
		1000	-0.04	-0.01	0.01	--	0.01	-0.02	-0.01	--	0.01	0.01	-0.06	--	0.07	0.07	-0.26	--
Poorly-Defined High Thresholds	50/50	200	0.01	-0.01	-0.01	--	0.00	-0.04	0.04	--	0.00	0.20	-0.20	--	0.01	0.15	-0.16	--
		500	0.01	0.00	-0.01	--	0.00	-0.02	0.02	--	0.00	0.16	-0.16	--	0.01	0.12	-0.13	--
		1000	0.01	0.00	-0.01	--	0.00	-0.02	0.02	--	0.00	0.14	-0.14	--	0.00	0.11	-0.11	--
	60/40	200	0.01	-0.01	-0.01	--	0.00	-0.05	0.05	--	0.00	0.18	-0.19	--	0.01	0.15	-0.16	--
		500	0.01	0.00	-0.01	--	0.00	-0.03	0.03	--	0.00	0.14	-0.15	--	0.01	0.13	-0.13	--
		1000	0.01	0.00	-0.01	--	0.00	-0.02	0.02	--	0.00	0.13	-0.13	--	0.00	0.11	-0.12	--
	80/20	200	0.01	-0.01	0.00	--	0.00	-0.09	0.09	--	0.00	0.17	-0.17	--	0.02	0.17	-0.19	--
		500	0.01	0.00	-0.01	--	0.00	-0.08	0.08	--	0.00	0.14	-0.14	--	0.01	0.11	-0.13	--
		1000	0.00	0.00	-0.01	--	0.00	-0.07	0.07	--	0.00	0.13	-0.13	--	0.01	0.09	-0.10	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table A.16d. Transition Probability Parameter Recovery: LMI Pattern B, Unordered Transition Matrix, Four-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Absolute Bias in Estimated Transition Matrix Parameters															
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#4 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#4 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#4 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4	C2#4 on C1#4
Well-Defined, Low Thresholds	50/50	200	-0.13	0.00	0.04	--	0.02	-0.09	0.04	--	0.02	0.14	-0.25	--	0.07	0.07	-0.25	--
		500	-0.04	-0.03	0.02	--	-0.01	-0.01	0.00	--	0.01	0.06	-0.12	--	0.03	0.03	-0.11	--
		1000	-0.01	-0.02	0.01	--	-0.01	0.01	-0.01	--	0.00	0.03	-0.05	--	0.01	0.01	-0.05	--
	60/40	200	-0.12	-0.01	0.04	--	0.02	-0.11	0.05	--	0.01	0.13	-0.24	--	0.09	0.08	-0.29	--
		500	-0.04	-0.02	0.02	--	-0.01	-0.01	0.00	--	0.00	0.05	-0.11	--	0.04	0.05	-0.15	--
		1000	-0.01	-0.02	0.01	--	-0.01	0.01	-0.01	--	0.00	0.02	-0.04	--	0.02	0.01	-0.07	--
	80/20	200	-0.10	-0.02	0.03	--	0.02	-0.12	0.06	--	0.02	0.10	-0.20	--	0.13	0.11	-0.43	--
		500	-0.05	-0.03	0.02	--	-0.01	-0.01	0.00	--	-0.01	0.03	-0.08	--	0.12	0.08	-0.31	--
		1000	-0.02	-0.02	0.01	--	-0.01	0.01	-0.02	--	-0.01	0.01	-0.04	--	0.07	0.05	-0.20	--
Well-Defined, Moderate Thresholds	50/50	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.02	--	0.00	-0.01	0.01	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	-0.01	--	-0.01	-0.02	0.03	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.03	--
	60/40	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	0.00	0.01	-0.02	--	0.00	-0.01	0.00	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.02	0.03	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.03	--
	80/20	200	0.00	-0.01	0.00	--	0.00	0.00	0.00	--	-0.01	0.01	-0.01	--	0.03	0.00	-0.06	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	-0.02	0.01	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	-0.02	0.02	--
Well-Defined, High Thresholds	50/50	200	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--
	60/40	200	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.02	0.03	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--
	80/20	200	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	-0.02	0.01	--
		500	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.03	--
		1000	0.00	0.00	0.00	--	0.00	0.00	0.00	--	0.00	0.00	0.00	--	-0.01	-0.03	0.04	--

Continues...

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Poorly-Defined, Moderate Thresholds	50/50	200	-0.09	-0.02	0.03	--	-0.02	-0.08	0.02	--	0.04	0.08	-0.26	--	0.07	0.04	-0.27	--
		500	-0.04	-0.02	0.02	--	-0.01	-0.02	0.00	--	0.02	0.02	-0.13	--	0.03	0.01	-0.14	--
		1000	-0.02	-0.01	0.01	--	-0.01	-0.01	-0.01	--	0.01	0.00	-0.07	--	0.02	-0.01	-0.06	--
	60/40	200	-0.11	-0.02	0.04	--	-0.02	-0.08	0.02	--	0.03	0.07	-0.23	--	0.10	0.05	-0.34	--
		500	-0.03	-0.02	0.02	--	-0.01	-0.02	-0.01	--	0.02	0.02	-0.14	--	0.04	0.03	-0.18	--
		1000	-0.02	-0.01	0.01	--	-0.01	-0.01	-0.01	--	0.01	0.00	-0.07	--	0.03	0.01	-0.10	--
	80/20	200	-0.10	-0.02	0.03	--	-0.03	-0.08	0.03	--	0.02	0.03	-0.21	--	0.13	0.11	-0.43	--
		500	-0.04	-0.02	0.02	--	-0.02	-0.01	-0.02	--	0.01	0.01	-0.11	--	0.10	0.07	-0.32	--
		1000	-0.03	-0.01	0.01	--	-0.01	-0.01	-0.01	--	0.00	-0.01	-0.05	--	0.08	0.04	-0.23	--
Poorly-Defined High Thresholds	50/50	200	0.01	-0.01	-0.01	--	0.00	-0.03	0.04	--	0.00	0.17	-0.17	--	-0.01	0.10	-0.09	--
		500	0.01	0.00	-0.01	--	0.00	-0.03	0.03	--	0.00	0.13	-0.13	--	-0.01	0.07	-0.06	--
		1000	0.01	0.00	-0.01	--	0.00	-0.02	0.02	--	-0.01	0.11	-0.11	--	-0.01	0.06	-0.05	--
	60/40	200	0.01	-0.01	-0.01	--	-0.01	-0.04	0.05	--	0.00	0.16	-0.16	--	-0.01	0.11	-0.11	--
		500	0.01	0.00	-0.01	--	0.00	-0.03	0.03	--	0.00	0.12	-0.12	--	-0.01	0.08	-0.07	--
		1000	0.01	0.00	-0.01	--	0.00	-0.02	0.02	--	0.00	0.10	-0.10	--	-0.01	0.06	-0.05	--
	80/20	200	0.01	-0.01	0.00	--	0.00	-0.07	0.08	--	0.00	0.14	-0.14	--	0.01	0.12	-0.14	--
		500	0.01	-0.01	-0.01	--	0.00	-0.07	0.07	--	0.00	0.11	-0.11	--	0.00	0.07	-0.07	--
		1000	0.01	0.00	-0.01	--	0.00	-0.05	0.06	--	0.00	0.09	-0.09	--	0.00	0.05	-0.05	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Appendix B: Standard Error Recovery Tables

Table B.1a. Item Response Standard Error Recovery: Well-Defined Classes with Low Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
Ordered	50/50	200	339	0.24	0.35	-0.26	0.34	-0.46	-0.48	-0.38	-0.14	0.18	-0.15	-0.30	-0.36	0.51	-0.40	0.03
		500	392	0.09	0.02	0.10	0.03	0.05	0.12	-0.10	0.08	0.04	0.12	-0.29	-0.39	0.17	0.17	0.14
		1000	446	0.01	0.01	0.06	0.14	0.08	0.08	0.14	0.06	0.09	0.08	0.12	-0.36	0.11	0.07	0.11
	60/40	200	460	0.49	0.46	-0.23	4.65	-0.33	-0.49	-0.31	-0.50	-0.29	-0.55	-0.54	-0.30	-0.41	-0.42	-0.31
		500	493	0.05	0.04	0.14	0.11	0.11	-0.36	-0.34	0.11	0.08	0.18	-0.34	-0.34	0.04	0.05	0.07
		1000	498	-0.02	0.00	-0.01	0.09	0.01	0.05	0.13	0.07	0.03	0.18	0.08	0.14	0.04	0.09	0.07
	80/20	200	93	0.29	0.20	0.30	0.10	0.01	-0.62	-0.53	-0.68	0.17	-0.55	-0.47	-0.35	-0.55	-0.51	0.27
		500	77	0.05	0.04	-0.05	-0.01	-0.01	0.06	-0.05	0.13	0.24	0.15	-0.67	2.51	0.01	0.04	-0.12
		1000	63	0.21	0.17	-0.09	-0.06	-0.03	-0.08	0.28	0.34	0.39	0.11	0.04	0.41	-0.07	-0.09	-0.07
Unordered	50/50	200	374	0.13	0.18	-0.34	-0.28	-0.43	-0.53	-0.54	-0.42	0.24	-0.66	0.07	-0.13	0.14	-0.15	0.27
		500	433	0.01	-0.01	0.12	0.15	0.09	0.13	-0.09	0.14	0.07	0.17	-0.37	-0.56	0.12	0.08	0.06
		1000	479	0.17	0.11	0.17	0.24	0.20	0.50	0.66	0.24	0.12	0.15	0.36	0.17	0.63	0.74	0.62
	60/40	200	471	0.31	1.55	0.10	-0.17	-0.62	-0.08	0.05	-0.32	-0.13	0.37	-0.40	-0.44	-0.36	0.07	-0.10
		500	494	0.14	0.05	0.17	0.13	0.11	-0.48	-0.34	0.25	0.20	0.27	-0.60	-0.40	0.03	0.09	0.09
		1000	491	-0.02	-0.01	0.00	0.08	0.04	0.04	0.11	0.06	0.04	0.14	0.15	0.08	0.04	0.05	0.12
	80/20	200	140	0.26	0.27	0.38	-0.57	0.06	-0.56	-0.62	-0.51	0.17	-0.46	-0.28	-0.20	-0.44	-0.35	0.26
		500	143	0.01	0.03	0.09	0.09	-0.04	0.10	0.07	0.28	0.31	0.28	-0.23	0.25	-0.02	-0.14	-0.14
		1000	143	0.23	0.22	0.00	-0.01	-0.03	-0.05	0.15	0.36	0.30	0.23	0.19	-0.44	-0.03	0.02	-0.06

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.1b. Item Response Standard Error Recovery: Well-Defined Classes with Low Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73
Ordered	50/50	200	370	0.51	0.42	0.84	0.61	-0.28	0.36	-0.47	-0.22	0.64	-0.38	-0.16	-0.01	0.42	0.61	0.54
		500	431	0.06	0.03	0.27	0.33	0.25	-0.31	0.18	0.11	0.14	0.15	-0.20	-0.20	0.11	0.18	0.14
		1000	461	0.02	0.03	0.13	0.18	0.12	0.06	0.12	0.03	0.08	0.08	-0.43	-0.18	0.10	0.05	0.09
	60/40	200	428	0.75	0.87	0.28	0.03	-0.04	0.12	-0.23	0.03	0.56	-0.13	-0.09	0.31	1.50	1.46	0.58
		500	464	0.08	0.11	0.28	0.23	0.26	-0.22	0.25	0.16	0.14	0.26	-0.41	-0.29	0.15	0.14	0.21
		1000	483	-0.02	-0.02	0.07	0.10	0.10	-0.01	0.04	0.01	0.05	0.05	-0.03	0.04	0.02	0.00	0.01
	80/20	200	468	1.04	0.52	-0.25	-0.12	-0.37	-0.14	-0.26	0.13	0.49	-0.31	-0.22	-0.12	-0.14	-0.22	-0.01
		500	491	0.19	0.27	0.14	0.19	0.12	-0.42	0.64	0.16	0.03	0.23	-0.22	0.19	0.15	0.06	0.06
		1000	477	0.01	-0.01	0.02	0.07	0.03	0.03	0.04	0.01	0.02	0.06	0.03	0.10	0.04	0.03	0.04
Unordered	50/50	200	350	0.88	0.62	0.04	-0.34	-0.05	-0.17	-0.42	-0.41	-0.11	-0.34	0.15	0.06	0.84	-0.10	0.73
		500	385	0.32	0.21	0.21	0.18	0.23	-0.05	0.06	0.13	0.23	0.23	0.10	1.94	0.46	0.55	0.60
		1000	436	0.04	0.04	0.23	0.20	0.19	0.20	0.11	0.02	0.06	0.11	0.37	-0.16	0.28	0.05	0.27
	60/40	200	400	0.41	1.11	0.15	-0.13	-0.07	-0.48	-0.11	-0.16	0.00	-0.29	-0.08	0.75	1.13	0.76	0.02
		500	451	0.07	0.07	0.15	0.17	0.15	-0.53	-0.35	0.09	0.06	0.11	0.04	-0.51	0.12	0.11	0.20
		1000	472	0.00	0.01	0.04	0.10	0.07	0.07	0.06	0.00	0.01	0.04	0.02	0.11	0.06	0.03	0.06
	80/20	200	459	-0.36	0.27	-0.51	-0.54	-0.37	0.40	-0.50	-0.45	-0.27	-0.44	0.05	-0.40	-0.32	0.43	-0.17
		500	490	0.09	0.04	0.20	0.19	0.18	-0.48	-0.12	-0.43	-0.24	0.18	-0.42	-0.60	0.14	0.07	0.23
		1000	484	0.01	-0.01	0.02	0.08	0.06	0.09	0.08	0.05	0.03	0.08	-0.44	0.05	0.07	0.04	0.07

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.2a. Item Response Standard Error Recovery: Well-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Ordered	50/50	200	465	-0.39	-0.35	0.23	-0.40	0.03	0.14	-0.42	0.08	0.07	0.13	-0.47	-0.39	-0.39	-0.39	-0.36
		500	487	-0.57	-0.57	0.02	-0.05	0.03	-0.11	-0.10	0.02	-0.06	-0.07	-0.08	-0.11	-0.57	-0.57	-0.57
		1000	499	-0.66	-0.67	-0.04	-0.06	-0.06	-0.17	-0.17	-0.09	-0.09	-0.10	-0.16	-0.19	-0.66	-0.66	-0.66
	60/40	200	500	0.11	0.06	0.14	-0.44	0.08	-0.31	-0.44	0.24	0.17	0.08	0.11	-0.37	0.13	0.14	0.16
		500	500	-0.01	0.01	0.05	-0.01	0.09	0.03	0.08	0.09	0.06	-0.05	0.05	0.13	0.00	-0.02	0.05
		1000	500	-0.03	0.01	0.02	0.03	0.04	0.03	0.03	-0.03	-0.03	-0.03	0.03	-0.01	0.01	0.04	0.05
	80/20	200	174	-0.49	-0.51	0.03	0.06	0.01	-0.52	-0.49	0.03	-0.01	-0.08	-0.73	-0.53	-0.25	-0.53	-0.16
		500	138	-0.47	-0.46	0.03	0.00	0.06	0.08	0.15	0.19	-0.02	-0.03	0.13	0.07	-0.24	-0.19	-0.23
		1000	102	0.09	0.19	0.08	-0.03	0.09	0.06	0.22	0.07	0.00	-0.04	0.05	0.06	0.13	-0.01	0.07
Unordered	50/50	200	485	-0.31	-0.30	0.06	-0.47	0.02	-0.48	-0.04	0.10	0.11	-0.01	-0.52	-0.28	-0.23	-0.22	-0.22
		500	500	-0.39	-0.38	0.00	-0.04	0.02	-0.05	-0.06	0.01	-0.03	-0.06	-0.35	-0.05	-0.34	-0.35	-0.35
		1000	500	-0.44	-0.44	-0.01	0.00	0.00	-0.06	-0.01	-0.08	-0.07	-0.05	-0.04	-0.10	-0.37	-0.38	-0.37
	60/40	200	500	0.04	-0.01	0.04	-0.46	0.01	-0.46	-0.14	0.07	0.08	0.03	0.21	0.21	0.06	0.09	0.10
		500	500	-0.03	-0.02	0.02	-0.03	0.06	0.00	-0.02	0.05	-0.01	-0.06	-0.05	-0.04	-0.05	-0.01	-0.02
		1000	500	-0.03	0.02	0.00	0.01	0.03	0.01	0.03	-0.05	-0.04	-0.04	0.01	-0.05	-0.01	0.03	0.02
	80/20	200	218	-0.39	-0.34	0.01	0.04	-0.07	-0.58	0.49	0.01	0.04	-0.08	-0.58	-0.39	-0.16	-0.63	-0.16
		500	219	-0.43	-0.44	0.07	-0.02	0.06	0.00	-0.01	0.15	-0.04	0.00	-0.10	-0.07	-0.24	-0.20	-0.20
		1000	186	0.04	0.08	0.04	-0.04	-0.01	0.05	0.11	-0.01	-0.03	0.01	0.08	-0.03	0.01	-0.03	-0.05

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.2b. Item Response Standard Error Recovery: Well-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Ordered	50/50	200	491	-0.26	-0.33	0.09	-0.17	0.10	-0.28	0.08	0.16	0.13	0.14	-0.28	-0.33	-0.26	-0.23	-0.23
		500	499	-0.39	-0.32	0.18	0.12	0.48	0.08	0.09	0.09	0.06	0.11	0.02	0.10	-0.32	-0.34	-0.38
		1000	500	-0.44	-0.44	0.06	0.05	0.09	-0.04	0.11	0.00	-0.02	-0.02	0.13	-0.06	-0.34	-0.33	-0.34
	60/40	200	497	-0.15	-0.18	0.20	-0.26	0.09	-0.30	0.09	0.11	0.20	0.17	0.15	-0.11	-0.16	-0.11	-0.10
		500	500	-0.24	-0.25	0.08	0.06	0.10	0.01	0.01	0.08	0.02	-0.02	-0.01	0.01	-0.22	-0.21	-0.21
		1000	500	-0.23	-0.22	0.04	0.16	0.11	0.14	0.15	0.01	-0.02	-0.04	0.07	0.09	-0.14	-0.15	-0.16
	80/20	200	500	0.07	0.06	0.17	-0.25	0.19	-0.12	0.64	0.14	0.18	0.25	0.51	-0.13	0.10	0.17	0.12
		500	500	0.07	0.12	0.11	0.04	0.15	0.04	0.06	0.15	0.09	0.01	0.09	0.06	0.05	0.08	0.05
		1000	500	0.11	0.16	0.12	0.20	0.06	0.64	0.74	0.09	0.06	0.07	0.35	0.37	0.06	0.15	0.12
Unordered	50/50	200	473	-0.29	-0.31	0.02	-0.47	-0.01	-0.39	0.10	0.08	0.04	0.02	0.02	-0.09	-0.28	-0.27	-0.26
		500	495	-0.46	-0.45	0.00	-0.06	0.02	-0.11	-0.08	0.02	-0.06	-0.09	-0.13	-0.08	-0.42	-0.41	-0.41
		1000	500	-0.52	-0.52	-0.04	-0.03	0.00	-0.13	-0.10	-0.06	-0.08	-0.08	-0.12	-0.13	-0.48	-0.48	-0.47
	60/40	200	489	-0.15	-0.19	0.02	-0.48	-0.02	-0.41	-0.29	0.06	0.08	0.06	-0.25	-0.48	-0.18	-0.15	-0.12
		500	500	-0.27	-0.25	0.01	-0.04	0.03	-0.06	-0.04	0.03	-0.03	-0.08	-0.10	-0.03	-0.26	-0.24	-0.25
		1000	500	-0.29	-0.28	-0.01	-0.01	0.02	-0.06	-0.04	-0.05	-0.05	-0.05	-0.04	-0.06	-0.27	-0.26	-0.25
	80/20	200	500	0.04	-0.03	0.02	-0.48	0.00	-0.34	-0.35	0.07	0.10	0.06	0.08	-0.40	-0.02	0.02	0.07
		500	500	-0.01	0.01	0.03	-0.01	0.05	-0.01	-0.01	0.04	0.00	-0.06	-0.04	-0.01	-0.01	0.01	0.01
		1000	500	0.01	0.07	0.02	0.02	0.03	0.00	0.03	-0.04	-0.03	-0.04	0.02	-0.03	0.00	0.04	0.04

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.3a. Item Response Standard Error Recovery: Well-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Ordered	50/50	200	488	-0.71	-0.70	-0.58	-0.67	-0.43	-0.60	-0.51	-0.45	-0.42	-0.49	-0.65	-0.49	-0.59	-0.57	-0.56
		500	499	-0.76	-0.76	-0.04	-0.06	-0.01	0.00	-0.43	0.02	0.00	-0.02	-0.32	-0.04	-0.60	-0.60	-0.60
		1000	500	-0.78	-0.78	-0.02	0.00	0.03	-0.03	0.09	-0.01	-0.02	0.01	-0.02	-0.03	-0.59	-0.60	-0.59
	60/40	200	500	-0.47	-0.37	-0.61	-0.65	-0.43	-0.56	-0.44	-0.42	-0.48	-0.51	-0.58	-0.44	-0.38	-0.40	-0.55
		500	500	-0.62	-0.62	-0.03	-0.05	0.01	0.02	-0.46	0.04	0.00	-0.02	-0.08	0.00	-0.61	-0.60	-0.61
		1000	500	-0.72	-0.71	-0.02	-0.03	0.04	-0.01	0.04	-0.01	-0.01	-0.01	-0.09	0.00	-0.69	-0.69	-0.69
	80/20	200	197	-0.40	-0.43	-0.01	-0.46	-0.56	-0.63	0.12	0.33	-0.18	0.00	-0.72	-0.58	-0.70	-0.64	-0.56
		500	159	0.16	0.12	0.75	0.01	0.38	0.29	0.25	0.04	1.48	0.02	-0.42	0.44	0.02	0.11	0.11
		1000	123	0.13	0.12	0.08	0.04	0.00	-0.05	0.03	0.02	-0.02	0.06	0.01	-0.01	0.03	0.02	0.02
Unordered	50/50	200	497	-0.59	-0.70	-0.60	-0.70	-0.33	-0.55	-0.49	-0.44	-0.47	-0.55	-0.33	-0.17	-0.50	-0.62	-0.45
		500	500	-0.64	-0.63	-0.04	-0.07	-0.02	-0.01	-0.37	0.01	-0.01	-0.03	-0.10	-0.05	-0.39	-0.39	-0.39
		1000	500	-0.26	-0.29	0.02	0.00	0.05	-0.01	0.05	-0.02	-0.03	0.01	-0.05	0.01	-0.10	-0.10	-0.11
	60/40	200	500	-0.40	-0.10	-0.59	-0.67	-0.32	-0.41	-0.43	-0.32	-0.46	-0.54	-0.45	-0.54	-0.39	-0.39	-0.38
		500	500	-0.27	-0.25	-0.03	-0.07	-0.01	-0.01	-0.43	0.02	-0.01	-0.03	-0.10	-0.03	-0.21	-0.18	-0.22
		1000	500	-0.20	-0.18	0.01	0.00	0.07	-0.01	0.03	-0.02	-0.03	0.01	-0.04	0.00	-0.13	-0.15	-0.17
	80/20	200	260	-0.30	-0.33	-0.51	-0.51	-0.50	-0.51	-0.32	-0.45	-0.11	-0.11	-0.76	-0.75	-0.69	-0.73	-0.67
		500	244	-0.02	-0.05	0.03	0.05	-0.10	0.02	0.05	-0.04	0.02	-0.06	-0.48	-0.09	-0.03	-0.02	0.04
		1000	247	0.02	0.01	0.07	-0.03	0.04	0.02	0.04	-0.05	-0.01	0.06	0.07	0.03	0.04	0.07	-0.05

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.3b. Item Response Standard Error Recovery: Well-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Ordered	50/50	200	497	-0.68	-0.67	-0.52	-0.58	-0.48	-0.37	-0.45	-0.14	-0.30	-0.58	-0.53	0.13	-0.63	-0.65	-0.53
		500	500	-0.24	-0.42	0.12	0.14	0.11	0.19	-0.26	0.13	0.14	0.07	-0.28	0.33	-0.33	-0.33	-0.35
		1000	500	-0.58	-0.55	0.05	0.07	0.08	0.00	0.06	-0.01	0.01	0.03	0.00	0.06	-0.28	-0.32	-0.29
	60/40	200	500	-0.62	-0.64	-0.52	-0.58	-0.45	-0.37	-0.47	-0.20	-0.25	-0.58	-0.56	-0.55	-0.67	-0.62	-0.56
		500	500	-0.67	-0.68	0.00	0.01	0.01	0.04	-0.13	0.07	0.04	0.01	-0.32	0.06	-0.46	-0.45	-0.47
		1000	500	-0.57	-0.55	0.08	0.04	0.07	0.15	0.16	0.03	0.05	0.03	0.05	0.20	-0.29	-0.32	-0.32
	80/20	200	500	-0.44	-0.46	-0.53	-0.54	-0.51	-0.36	-0.51	-0.43	-0.32	-0.57	-0.36	-0.54	-0.51	-0.35	-0.51
		500	500	-0.54	-0.54	-0.01	0.01	0.04	0.04	-0.14	0.07	0.04	0.02	-0.45	0.06	-0.45	-0.43	-0.45
		1000	500	-0.63	-0.63	0.07	0.04	0.12	0.01	0.05	0.04	0.03	0.03	-0.05	0.08	-0.51	-0.51	-0.51
Unordered	50/50	200	491	-0.73	-0.66	-0.54	-0.63	-0.55	-0.46	-0.49	-0.44	-0.53	-0.66	-0.56	-0.46	-0.68	-0.69	-0.57
		500	500	-0.70	-0.71	-0.02	-0.03	-0.02	0.00	-0.38	0.01	-0.03	-0.01	-0.11	-0.04	-0.50	-0.49	-0.50
		1000	500	-0.56	-0.56	0.03	0.02	0.03	-0.02	0.00	-0.03	-0.01	0.02	-0.08	0.03	-0.31	-0.33	-0.31
	60/40	200	499	-0.61	-0.62	-0.52	-0.60	-0.54	2.98	-0.49	-0.44	-0.25	-0.61	-0.60	-0.51	-0.68	-0.67	-0.51
		500	500	-0.67	-0.68	-0.03	-0.05	-0.01	0.00	-0.35	0.00	-0.01	0.00	-0.43	-0.01	-0.51	-0.50	-0.51
		1000	500	-0.57	-0.56	0.03	0.01	0.04	-0.02	0.00	-0.03	-0.01	0.02	-0.17	0.00	-0.34	-0.36	-0.35
	80/20	200	500	-0.44	-0.45	-0.53	-0.63	-0.46	-0.44	-0.50	-0.44	-0.47	-0.61	-0.47	-0.09	-0.59	-0.35	-0.50
		500	500	-0.53	-0.54	-0.04	-0.05	0.00	0.02	-0.03	0.01	-0.01	-0.01	-0.46	0.00	-0.45	-0.44	-0.46
		1000	500	-0.62	-0.61	0.00	0.01	0.04	-0.03	-0.01	-0.03	-0.01	0.02	-0.12	0.00	-0.51	-0.51	-0.51

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.4a. Item Response Standard Error Recovery: Poorly-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50
Ordered	50/50	200	471	-0.24	0.74	1.02	-0.37	0.66	0.13	-0.29	0.54	-0.42	-0.17	-0.05	-0.21	0.38	-0.45	-0.30
		500	496	-0.30	0.53	0.14	0.32	0.14	0.46	0.24	0.21	0.24	0.65	-0.26	0.31	0.24	-0.60	0.13
		1000	498	-0.14	0.16	0.04	0.09	0.07	0.08	-0.34	0.14	0.14	0.14	0.16	0.31	0.14	-0.43	0.18
	60/40	200	492	-0.51	0.76	0.49	1.81	0.85	0.17	-0.53	0.65	0.83	-0.17	0.01	0.14	-0.26	-0.41	1.64
		500	500	-0.47	0.22	0.04	0.11	0.12	0.14	-0.40	0.13	0.28	0.15	0.32	0.38	0.14	-0.55	0.15
		1000	500	-0.53	0.08	0.03	0.11	0.03	0.11	-0.44	0.01	0.08	-0.01	0.15	0.13	0.06	-0.61	0.14
	80/20	200	203	0.79	10.78	1.54	16.35	5.50	2.10	-0.21	0.49	-0.29	1.12	0.58	-0.01	1.00	0.09	0.19
		500	214	-0.17	0.50	0.70	0.38	0.21	0.66	-0.12	2.54	1.44	1.73	-0.60	0.86	1.05	-0.39	1.13
		1000	221	-0.37	0.22	0.58	0.45	0.07	0.10	-0.47	0.16	0.29	0.02	0.84	0.16	0.54	-0.43	0.49
Unordered	50/50	200	473	-0.42	0.22	0.22	-0.49	0.25	0.32	-0.69	0.26	-0.13	-0.46	-0.48	-0.47	-0.43	-0.59	-0.45
		500	499	-0.38	0.11	0.05	0.13	0.05	0.06	-0.42	0.17	0.25	0.17	-0.17	0.29	0.10	-0.61	0.13
		1000	500	-0.47	0.07	0.05	0.18	0.00	0.03	-0.47	-0.01	0.04	-0.01	0.16	0.04	0.04	-0.62	0.08
	60/40	200	496	1.10	0.30	0.15	0.31	0.20	0.29	-0.66	-0.55	0.00	-0.37	-0.32	0.09	0.15	-0.32	-0.42
		500	498	-0.48	0.22	0.03	0.12	0.08	0.22	-0.52	0.17	0.41	0.08	-0.44	0.38	0.10	-0.55	0.26
		1000	499	-0.55	0.12	0.06	0.14	0.03	0.10	-0.50	0.00	0.11	0.02	0.18	0.09	0.07	-0.49	0.05
	80/20	200	253	-0.40	-0.54	0.77	-0.60	0.12	0.19	-0.47	0.04	-0.22	-0.27	-0.10	-0.42	0.11	-0.62	-0.25
		500	305	-0.49	0.18	0.16	0.30	0.09	0.05	-0.45	0.17	0.46	0.08	-0.10	0.36	0.29	-0.40	0.40
		1000	353	-0.33	0.16	0.31	0.37	0.09	0.05	-0.46	0.14	0.29	0.06	-0.28	0.25	0.38	-0.33	0.40

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.4b. Item Response Standard Error Recovery: Poorly-Defined Classes with Moderate Thresholds, Three-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50
Ordered	50/50	200	485	3.18	0.27	0.26	-0.31	-0.29	0.10	-0.60	0.27	-0.49	-0.52	-0.28	-0.47	0.23	-0.52	0.51
		500	499	-0.47	0.14	0.09	0.24	0.10	0.08	-0.51	0.08	0.36	0.19	0.44	0.44	0.14	-0.57	0.23
		1000	500	-0.51	0.01	0.06	0.16	0.05	0.04	-0.09	-0.04	0.05	0.06	0.27	0.13	0.07	-0.27	0.08
	60/40	200	491	-0.50	1.07	0.97	0.90	0.30	0.98	-0.26	0.81	0.40	-0.20	0.42	-0.04	0.68	-0.35	0.75
		500	499	0.74	0.55	0.33	0.40	0.12	1.12	-0.55	0.67	0.26	0.43	0.96	1.74	0.26	-0.25	0.79
		1000	500	-0.48	0.07	0.02	0.16	0.10	0.22	-0.25	0.28	0.54	0.21	0.16	0.11	0.34	-0.16	0.07
	80/20	200	497	0.30	0.58	0.25	0.40	0.49	0.62	-0.60	0.14	-0.31	-0.14	-0.23	2.20	0.38	-0.55	0.51
		500	499	-0.43	0.08	0.03	0.14	0.08	0.13	-0.64	0.04	0.21	0.16	0.22	0.23	0.08	-0.52	0.12
		1000	500	-0.46	0.06	0.02	0.11	0.06	0.12	-0.30	-0.03	0.06	0.06	0.11	0.09	0.02	-0.34	0.06
Unordered	50/50	200	473	-0.51	0.57	0.33	-0.51	0.50	0.55	-0.17	0.27	-0.36	-0.48	-0.19	-0.23	0.38	-0.27	0.46
		500	498	-0.40	0.12	0.08	0.17	0.09	0.04	-0.55	0.06	0.18	0.09	-0.29	0.23	0.16	-0.22	0.22
		1000	500	-0.42	0.00	0.02	0.07	0.03	0.00	-0.54	-0.04	0.02	-0.01	0.06	0.11	0.04	-0.41	0.06
	60/40	200	476	0.03	2.96	1.14	1.19	0.54	2.35	1.25	1.42	0.26	-0.12	12.48	0.63	1.74	-0.34	0.68
		500	499	-0.45	0.12	0.08	0.21	0.06	0.04	-0.49	0.03	0.21	0.11	-0.38	-0.45	0.09	-0.59	0.18
		1000	498	-0.19	0.02	0.02	0.07	0.02	-0.01	-0.52	-0.06	0.02	-0.03	0.03	0.07	0.02	-0.39	0.06
	80/20	200	490	-0.31	0.34	0.16	0.33	0.44	0.88	-0.71	0.37	-0.15	-0.39	-0.09	0.50	0.36	-0.45	0.48
		500	500	-0.55	0.06	-0.02	0.07	0.02	-0.01	-0.61	0.01	0.12	0.02	0.13	-0.64	-0.01	-0.49	0.10
		1000	499	-0.31	0.05	0.06	0.11	0.02	0.04	-0.49	0.02	0.21	0.02	0.16	0.15	0.12	-0.52	0.06

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.5a. Item Response Standard Error Recovery: Poorly-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern A

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05
Ordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	48	0.07	-0.69	-0.18	0.04	-0.23	-0.82	0.06	-0.92	-0.12	2.44	-0.94	-0.77	-0.27	-0.84	-0.63
		500	2	-0.35	-0.67	0.82	10.18	-0.64	0.83	-0.08	3.49	-0.09	2.13	-0.55	0.55	0.14	-0.26	2.40
		1000	0															
	80/20	200	0															
		500	0															
		1000	0															
Unordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	267	0.01	-0.87	-0.02	-0.06	0.05	-0.63	-0.59	-0.67	-0.71	-0.76	-0.93	-0.71	-0.78	-0.72	-0.14
		500	167	0.00	-0.49	0.07	0.03	0.03	0.31	0.33	0.09	0.13	-0.44	-0.84	0.28	0.09	-0.01	0.44
		1000	116	0.07	-0.16	0.01	0.02	0.00	0.25	0.07	0.09	0.07	-0.34	-0.73	-0.01	0.02	-0.03	0.40
	80/20	200	0															
		500	0															
		1000	0															

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.5b. Item Response Standard Error Recovery: Poorly-Defined Classes with High Thresholds, Three-Class Solutions, Non-Invariance Pattern B

				Relative Bias in Estimated Time 1 Item Response Logit Standard Errors														
				Class 1 Population Item Probabilities					Class 2 Population Item Probabilities					Class 3 Population Item Probabilities				
Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05
Ordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	4	2.22	-0.08	-0.28	0.01	-0.19	-0.31	0.57	0.26	-0.24	-0.91	-0.82	0.04	-0.48	-0.14	0.28
		500	0															
		1000	0															
	80/20	200	161	0.01	-0.84	-0.02	0.02	-0.17	0.29	0.22	-0.75	-0.12	-0.64	-0.87	-0.69	-0.49	0.35	-0.17
		500	60	-0.05	-0.11	0.18	-0.11	-0.09	0.18	-0.06	-0.04	0.02	-0.43	-0.85	0.02	-0.02	0.01	0.22
		1000	18	0.00	0.06	0.37	-0.08	-0.12	0.11	-0.04	0.36	0.03	-0.85	-0.62	0.30	0.36	-0.03	0.49
Unordered	50/50	200	0															
		500	0															
		1000	0															
	60/40	200	3	0.93	-0.37	0.49	-0.11	-0.39	-0.28	0.61	1.40	-0.29	-0.90	--	0.07	-0.46	0.07	1.21
		500	0															
		1000	0															
	80/20	200	137	0.00	-0.87	-0.06	0.04	-0.65	0.06	0.05	-0.78	-0.12	-0.83	-0.87	0.00	-0.63	-0.11	-0.62
		500	42	-0.11	-0.23	0.04	-0.01	-0.09	0.38	0.19	0.07	0.12	-0.36	-0.79	-0.03	0.11	-0.07	0.60
		1000	10	-0.15	0.26	0.01	-0.19	-0.07	0.01	0.08	0.71	0.11	-0.03	-0.46	0.22	0.49	0.03	0.28

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.6a. Item Response Standard Error Recovery: Well-Defined Classes with Low Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	368	-0.56	-0.75	-0.41	-0.26	-0.61	-0.51	-0.54	-0.46	-0.58	0.38	-0.67	-0.64	-0.66	-0.75	-0.55	--	--	--	--	--
		500	468	0.09	-0.35	0.32	-0.02	0.76	-0.18	0.02	1.05	0.80	0.46	-0.30	-0.10	-0.21	0.41	0.45	--	--	--	--	--
		1000	474	0.61	0.76	0.28	0.13	0.51	1.22	0.80	0.59	0.72	0.21	0.50	0.19	0.41	0.61	0.37	--	--	--	--	--
	60/40	200	186	-0.67	-0.85	-0.80	-0.57	-0.76	-0.60	-0.38	-0.80	3.72	-0.71	-0.52	-0.64	-0.82	-0.74	-0.81	--	--	--	--	--
		500	286	-0.62	-0.72	0.57	-0.40	0.26	0.11	-0.41	0.15	0.12	0.06	-0.56	-0.72	-0.67	-0.69	-0.75	--	--	--	--	--
		1000	389	-0.57	-0.68	0.18	0.14	0.32	0.14	0.18	0.18	0.11	0.22	0.02	0.16	-0.57	-0.68	-0.29	--	--	--	--	--
	80/20	200	433	-0.54	1.06	-0.16	-0.44	-0.39	-0.66	-0.63	-0.53	-0.47	-0.45	-0.46	-0.59	-0.54	-0.21	-0.31	--	--	--	--	--
		500	468	0.17	0.27	0.13	0.07	0.08	0.12	0.18	0.03	0.04	0.07	0.10	0.29	0.11	0.09	0.10	--	--	--	--	--
		1000	473	0.51	0.59	0.10	0.13	0.13	0.23	0.17	0.07	0.14	0.12	0.25	0.37	0.19	0.28	0.24	--	--	--	--	--
Unordered	50/50	200	314	-0.69	-0.78	-0.70	-0.47	-0.67	-0.59	0.03	-0.63	-0.44	-0.63	-0.60	-0.62	-0.80	-0.71	-0.77	--	--	--	--	--
		500	439	-0.57	-0.47	0.52	-0.40	0.93	-0.44	0.24	0.86	0.67	0.80	-0.36	-0.23	-0.33	0.05	-0.49	--	--	--	--	--
		1000	483	0.30	0.32	0.09	0.08	0.07	0.03	0.12	0.10	0.04	0.11	0.09	-0.27	-0.65	0.21	0.16	--	--	--	--	--
	60/40	200	115	-0.61	-0.72	-0.78	-0.70	-0.70	-0.67	-0.69	-0.71	-0.49	-0.70	-0.46	-0.61	-0.80	-0.77	-0.86	--	--	--	--	--
		500	141	-0.68	-0.74	0.24	0.19	0.38	0.03	-0.62	0.25	0.17	0.12	-0.61	-0.65	-0.73	-0.29	-0.71	--	--	--	--	--
		1000	236	-0.73	-0.76	0.19	0.43	0.36	0.18	0.33	0.17	0.26	0.25	0.44	0.01	-0.22	-0.56	0.02	--	--	--	--	--
	80/20	200	432	-0.51	-0.60	-0.63	-0.48	-0.51	-0.73	-0.76	-0.71	-0.56	-0.67	-0.59	-0.55	-0.67	-0.58	-0.38	--	--	--	--	--
		500	468	0.36	0.42	0.18	0.16	0.16	0.17	0.27	0.17	0.13	0.26	0.17	-0.35	0.30	0.14	0.16	--	--	--	--	--
		1000	477	0.21	0.19	0.11	0.12	0.08	0.74	0.52	0.10	0.12	0.12	0.27	0.36	0.17	0.18	0.17	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.6b. Item Response Standard Error Recovery: Well-Defined Classes with Low Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.27	0.27	0.27
Ordered	50/50	200	349	-0.32	0.14	-0.35	2.42	1.40	-0.53	-0.19	-0.37	-0.17	-0.41	0.36	0.80	1.02	-0.44	-0.58	13.86	-0.54	0.16	-0.51	0.00
		500	451	-0.61	-0.35	0.35	0.33	0.23	-0.22	0.04	0.37	0.42	0.42	-0.03	-0.44	-0.09	-0.28	0.80	-0.59	-0.29	-0.30	-0.35	-0.43
		1000	469	0.34	0.17	0.06	0.12	0.06	0.10	0.11	0.07	0.04	0.11	0.01	0.17	0.20	0.34	0.38	0.42	-0.02	0.27	-0.06	0.20
	60/40	200	305	-0.79	-0.77	-0.64	-0.51	-0.70	-0.72	-0.66	-0.35	-0.71	-0.69	-0.59	-0.64	-0.73	-0.84	-0.74	-0.72	-0.57	2.17	-0.72	-0.71
		500	427	-0.27	-0.18	0.40	-0.26	0.62	-0.39	-0.10	0.28	-0.45	0.80	-0.16	-0.46	-0.25	-0.28	1.25	-0.27	-0.25	-0.03	-0.32	-0.27
		1000	470	0.26	0.01	0.05	0.10	0.04	0.10	0.07	0.04	0.06	0.11	0.00	0.06	-0.14	0.09	0.27	-0.31	-0.13	-0.33	-0.46	-0.50
	80/20	200	154	-0.78	-0.75	-0.79	-0.66	-0.79	-0.49	-0.71	-0.41	-0.50	-0.77	-0.55	-0.60	-0.74	-0.76	-0.83	-0.67	-0.58	-0.71	-0.73	-0.74
		500	237	-0.66	-0.72	0.16	-0.68	0.06	-0.59	-0.54	0.16	0.03	0.15	-0.47	-0.53	-0.65	-0.56	-0.28	-0.60	-0.57	-0.64	-0.62	-0.57
		1000	372	-0.64	-0.70	0.25	0.14	0.15	0.15	0.22	0.18	0.33	0.19	0.18	0.24	-0.48	-0.68	0.38	-0.29	0.45	-0.45	0.41	-0.18
Unordered	50/50	200	364	-0.24	-0.54	-0.54	-0.62	-0.47	-0.58	-0.63	-0.66	-0.58	-0.56	-0.64	-0.59	-0.73	-0.69	-0.61	-0.33	-0.28	-0.66	-0.69	-0.58
		500	474	-0.54	0.39	0.16	0.22	0.18	-0.64	-0.16	0.59	-0.54	0.19	-0.45	-0.44	-0.41	-0.54	-0.03	-0.42	-0.32	-0.31	-0.37	-0.57
		1000	492	0.17	-0.33	0.02	0.08	0.04	0.02	0.07	0.00	0.02	0.07	-0.43	-0.31	0.07	0.08	0.16	-0.15	-0.21	0.04	-0.45	0.12
	60/40	200	320	-0.68	-0.70	-0.58	-0.54	-0.57	-0.42	-0.72	-0.59	-0.64	-0.61	-0.55	-0.58	-0.53	-0.81	-0.68	-0.74	0.23	-0.33	-0.63	-0.62
		500	458	-0.64	-0.73	0.10	-0.43	0.07	-0.23	-0.29	-0.40	-0.60	0.05	-0.46	-0.61	-0.51	-0.59	-0.62	-0.39	-0.59	-0.45	-0.48	-0.59
		1000	488	0.64	0.78	0.18	0.16	0.14	0.33	0.33	0.37	0.17	0.39	-0.15	-0.26	0.20	0.73	1.17	0.02	0.50	0.46	0.14	-0.26
	80/20	200	161	-0.76	-0.77	-0.69	-0.68	-0.71	-0.42	-0.65	-0.73	-0.34	-0.58	-0.67	-0.59	-0.79	-0.80	-0.57	-0.73	-0.69	-0.85	-0.74	-0.73
		500	239	0.04	-0.41	0.74	-0.61	-0.57	-0.69	-0.05	-0.56	-0.50	-0.38	-0.39	0.29	-0.54	-0.68	-0.54	-0.22	-0.41	-0.45	-0.62	-0.09
		1000	367	-0.60	-0.43	0.33	0.40	0.23	0.06	0.12	0.13	0.09	0.15	-0.05	-0.25	-0.61	-0.55	-0.48	-0.40	-0.29	-0.50	-0.52	-0.43

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.7a. Item Response Standard Error Recovery: Well-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	410	0.16	0.49	-0.45	-0.06	0.70	-0.30	-0.27	0.51	0.63	0.51	0.00	0.34	1.32	1.70	-0.22	--	--	--	--	--
		500	458	1.06	0.99	0.15	0.00	0.19	0.01	0.01	0.09	0.08	0.00	0.08	0.00	0.27	0.58	0.33	--	--	--	--	--
		1000	478	0.05	0.09	0.02	0.03	0.02	0.03	0.03	-0.04	-0.03	-0.03	-0.02	-0.01	0.04	0.04	-0.02	--	--	--	--	--
	60/40	200	415	-0.48	-0.56	-0.25	-0.36	0.21	-0.57	0.40	0.17	0.62	0.32	2.67	-0.41	-0.13	-0.12	-0.07	--	--	--	--	--
		500	446	0.40	0.29	0.10	0.01	0.08	0.03	0.00	0.06	-0.01	-0.06	-0.02	0.05	0.18	0.17	0.02	--	--	--	--	--
		1000	470	0.27	0.35	0.09	0.07	0.09	1.13	0.09	0.17	0.16	0.29	0.01	0.88	0.15	0.20	0.12	--	--	--	--	--
	80/20	200	388	0.07	-0.46	0.08	-0.32	0.27	-0.37	0.14	0.22	0.18	0.29	-0.49	0.21	-0.36	-0.29	0.29	--	--	--	--	--
		500	441	0.18	0.18	0.06	0.00	0.11	0.06	0.02	0.06	0.00	-0.03	0.08	0.01	0.09	0.02	0.05	--	--	--	--	--
		1000	474	0.16	0.21	0.03	0.08	0.04	0.09	0.12	-0.04	-0.03	-0.03	0.06	0.00	0.10	0.08	0.02	--	--	--	--	--
Unordered	50/50	200	423	0.55	0.36	-0.29	-0.04	0.71	-0.49	-0.12	0.30	0.51	0.62	-0.54	-0.40	-0.13	-0.46	-0.17	--	--	--	--	--
		500	470	0.13	0.60	0.12	-0.01	0.08	0.02	-0.02	0.07	0.01	-0.05	0.05	-0.02	0.11	0.09	-0.02	--	--	--	--	--
		1000	492	0.03	0.08	0.01	0.03	0.02	0.03	0.04	-0.04	-0.03	-0.04	0.02	-0.03	0.04	0.04	-0.02	--	--	--	--	--
	60/40	200	368	-0.76	-0.71	-0.49	-0.49	0.09	-0.52	-0.17	0.08	0.18	0.01	-0.49	-0.51	-0.68	-0.70	-0.59	--	--	--	--	--
		500	475	-0.49	-0.47	0.11	0.05	0.16	0.03	0.08	0.09	0.06	0.00	0.01	0.07	-0.17	0.25	0.25	--	--	--	--	--
		1000	488	0.05	0.09	0.01	0.02	0.03	0.01	0.04	-0.04	-0.03	-0.04	0.01	-0.03	0.07	0.13	0.11	--	--	--	--	--
	80/20	200	402	0.35	-0.40	0.12	-0.46	0.08	0.36	0.07	0.09	0.13	0.03	-0.56	-0.12	-0.24	-0.42	-0.04	--	--	--	--	--
		500	467	0.01	0.00	0.02	-0.03	0.07	0.02	0.00	0.06	-0.02	-0.03	0.06	0.03	0.10	0.06	0.08	--	--	--	--	--
		1000	479	0.04	0.08	0.02	0.03	0.02	0.03	0.08	-0.05	-0.03	-0.03	0.02	0.02	0.07	0.05	-0.02	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.7b. Item Response Standard Error Recovery: Well-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.12	0.12	0.12
Ordered	50/50	200	489	-0.26	-0.35	0.15	-0.26	0.15	-0.29	0.18	0.04	0.13	0.09	0.39	-0.27	0.39	0.03	0.69	-0.55	-0.47	-0.54	-0.37	-0.42
		500	482	0.36	0.15	0.09	0.12	0.13	0.17	0.12	0.13	0.08	0.04	0.24	0.20	0.81	0.68	0.88	-0.47	-0.13	1.26	1.63	0.99
		1000	484	0.14	0.28	0.21	0.11	0.28	0.47	0.39	0.32	0.21	0.30	0.35	0.10	0.44	0.28	0.22	0.07	0.24	0.80	0.70	1.17
	60/40	200	487	-0.11	-0.42	0.06	-0.46	0.08	-0.30	0.11	0.06	0.11	0.07	0.28	-0.22	0.18	-0.49	-0.21	-0.39	-0.70	-0.66	-0.43	-0.43
		500	480	0.02	0.05	0.03	0.01	0.13	0.01	0.03	0.07	0.02	-0.05	0.09	0.04	0.19	0.21	0.21	-0.58	-0.43	-0.40	-0.19	-0.07
		1000	478	1.08	1.90	0.71	0.58	0.30	1.43	1.65	0.07	0.71	0.47	0.31	1.57	9.05	14.75	13.17	2.51	3.47	14.93	10.83	10.50
	80/20	200	459	-0.38	-0.54	0.19	0.20	0.26	-0.26	0.28	0.21	0.28	0.21	0.26	0.38	-0.25	-0.57	-0.58	-0.55	-0.44	-0.41	-0.25	-0.29
		500	485	1.68	1.07	0.26	0.89	0.39	0.37	0.45	0.32	0.18	0.05	0.73	0.22	1.23	1.23	1.06	-0.06	-0.13	3.01	0.95	0.60
		1000	492	0.78	4.67	0.52	0.44	0.48	0.64	0.45	0.12	0.30	0.19	0.76	0.17	1.32	0.47	0.89	5.10	0.57	0.70	0.12	-0.05
Unordered	50/50	200	495	0.40	-0.27	0.11	-0.26	0.28	-0.17	0.40	0.45	0.32	0.67	0.20	0.23	0.59	0.28	-0.10	0.73	0.23	-0.31	1.42	-0.29
		500	494	0.03	0.05	0.03	-0.02	0.09	0.02	0.03	0.05	0.01	-0.06	0.04	0.08	0.13	0.18	0.07	-0.49	-0.41	-0.23	0.14	0.20
		1000	498	0.04	0.10	0.03	0.03	0.04	0.02	0.26	-0.02	-0.02	0.16	0.33	0.06	0.18	0.11	0.19	0.06	0.14	0.14	0.13	0.17
	60/40	200	492	-0.18	-0.39	0.14	-0.43	0.11	-0.13	0.02	0.15	0.13	0.23	0.32	3.00	0.60	-0.37	0.01	-0.47	-0.51	-0.65	-0.45	-0.55
		500	496	0.06	0.09	0.04	-0.02	0.10	0.04	0.05	0.05	0.01	-0.06	0.08	0.07	0.16	0.22	0.18	-0.41	-0.29	-0.19	-0.18	-0.04
		1000	500	0.12	0.09	0.01	0.03	0.04	0.04	0.06	-0.03	-0.02	-0.03	0.08	0.04	0.21	0.15	0.12	0.13	0.27	0.14	-0.27	0.23
	80/20	200	457	-0.54	-0.41	0.31	-0.38	0.15	-0.46	-0.31	0.15	0.16	0.23	-0.02	0.42	-0.12	-0.57	-0.41	-0.57	-0.49	-0.51	-0.52	-0.39
		500	494	0.94	1.09	0.14	0.57	0.58	0.25	0.25	0.42	0.16	0.11	0.31	0.32	1.37	0.93	1.47	-0.02	0.10	1.23	0.03	-0.06
		1000	495	0.13	0.15	0.02	0.08	0.04	0.02	0.06	-0.04	-0.03	-0.04	0.05	-0.03	0.26	0.13	0.14	-0.51	-0.48	-0.33	-0.41	-0.33

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.8a. Item Response Standard Error Recovery: Well-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	289	-0.17	0.31	-0.36	-0.48	-0.21	-0.47	-0.53	-0.23	0.04	-0.05	-0.64	-0.12	-0.01	-0.09	-0.51	--	--	--	--	--
		500	403	0.46	0.58	-0.01	0.00	0.20	0.08	-0.46	0.64	0.22	0.16	-0.41	0.00	0.06	0.02	0.00	--	--	--	--	--
		1000	441	0.11	0.03	0.05	-0.01	0.08	-0.02	0.05	-0.01	-0.01	-0.01	-0.05	0.02	0.06	0.01	0.00	--	--	--	--	--
	60/40	200	290	-0.60	-0.13	-0.36	-0.62	-0.55	-0.50	-0.38	-0.18	-0.41	-0.60	-0.43	-0.61	-0.56	-0.37	-0.58	--	--	--	--	--
		500	398	0.29	1.08	0.06	1.11	0.09	0.10	-0.41	0.08	0.06	0.03	0.59	0.12	1.48	0.17	1.17	--	--	--	--	--
		1000	451	0.44	0.30	0.06	0.06	0.16	0.03	0.06	0.01	-0.01	0.01	0.00	0.12	0.21	0.10	0.05	--	--	--	--	--
	80/20	200	324	-0.32	-0.38	-0.55	-0.64	-0.59	-0.53	-0.43	-0.56	-0.43	-0.43	-0.76	-0.69	-0.67	-0.73	-0.75	--	--	--	--	--
		500	389	0.19	0.01	-0.02	-0.05	0.01	0.08	-0.01	-0.01	0.00	-0.03	-0.45	-0.04	0.02	0.01	0.01	--	--	--	--	--
		1000	419	0.14	-0.01	0.03	-0.01	0.08	-0.03	0.21	0.00	0.01	-0.03	0.15	-0.03	0.03	0.05	-0.02	--	--	--	--	--
Unordered	50/50	200	313	-0.23	0.68	0.26	-0.57	0.57	-0.05	1.78	1.20	0.71	-0.01	0.11	-0.38	-0.33	-0.49	-0.23	--	--	--	--	--
		500	432	0.66	0.22	0.00	0.01	0.02	0.00	-0.34	0.06	0.00	0.01	-0.20	0.00	0.32	0.48	0.20	--	--	--	--	--
		1000	476	1.23	0.54	0.09	0.03	0.13	0.00	0.15	-0.01	-0.03	0.02	0.10	0.04	0.14	0.30	0.31	--	--	--	--	--
	60/40	200	345	-0.77	-0.53	-0.46	-0.53	-0.55	-0.59	-0.52	-0.38	-0.52	-0.40	-0.49	-0.44	-0.54	2.39	-0.44	--	--	--	--	--
		500	430	0.18	1.48	2.85	1.52	2.54	1.86	0.57	1.31	2.03	1.32	3.15	1.39	2.69	-0.41	6.45	--	--	--	--	--
		1000	479	0.17	0.39	0.14	0.05	0.15	0.07	0.08	0.02	0.01	0.06	0.03	0.09	0.15	0.25	0.18	--	--	--	--	--
	80/20	200	312	-0.47	-0.27	-0.63	-0.66	-0.52	-0.32	-0.45	-0.37	-0.45	-0.28	-0.68	-0.61	-0.55	0.20	1.43	--	--	--	--	--
		500	413	0.46	0.15	0.03	-0.04	0.02	0.21	0.47	0.03	0.02	-0.02	0.11	0.19	0.26	0.06	0.24	--	--	--	--	--
		1000	447	0.15	0.07	0.04	-0.01	0.08	-0.01	0.07	-0.01	0.01	-0.01	0.01	-0.02	0.08	0.05	-0.01	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.8b. Item Response Standard Error Recovery: Well-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.05	0.05	0.05
Ordered	50/50	200	445	2.24	1.73	-0.36	-0.65	-0.48	-0.30	-0.27	-0.49	-0.28	-0.60	-0.59	-0.57	-0.46	0.00	-0.34	-0.45	-0.46	-0.76	-0.82	-0.78
		500	499	0.77	0.52	-0.02	-0.01	0.03	0.11	0.03	0.05	0.03	0.00	-0.36	0.15	0.05	0.10	0.06	-0.60	-0.60	-0.61	-0.63	-0.66
		1000	498	0.44	0.27	0.07	0.02	0.08	0.11	0.14	-0.01	0.01	0.02	0.08	0.20	0.18	0.09	0.09	-0.27	-0.12	0.22	0.15	0.21
	60/40	200	432	3.15	5.40	-0.28	-0.63	-0.51	0.16	-0.31	-0.50	-0.29	-0.56	-0.54	-0.42	-0.40	-0.40	-0.36	-0.36	-0.17	-0.71	-0.73	-0.69
		500	499	0.71	0.68	0.01	0.02	0.05	0.12	0.04	0.06	0.04	0.02	-0.40	0.22	0.34	0.27	0.08	-0.61	-0.61	-0.68	-0.57	-0.51
		1000	498	0.27	0.21	0.06	0.02	0.08	0.11	0.15	-0.01	0.01	0.02	0.11	0.24	0.36	0.24	0.32	-0.47	-0.25	0.38	0.46	-0.04
	80/20	200	379	0.89	1.65	-0.28	-0.61	-0.59	0.05	-0.23	-0.50	-0.34	-0.59	-0.38	-0.30	-0.47	-0.63	-0.19	-0.65	-0.74	-0.83	-0.83	-0.78
		500	494	1.03	0.70	0.07	0.01	0.11	0.14	0.10	0.08	0.07	0.03	-0.40	0.25	0.28	0.27	0.27	-0.66	-0.68	-0.59	-0.61	-0.69
		1000	498	0.55	0.74	0.08	0.06	0.17	0.46	0.35	0.12	0.07	0.06	0.11	1.40	2.41	3.24	2.45	-0.47	0.34	2.23	0.44	0.91
Unordered	50/50	200	486	0.42	0.28	-0.37	-0.60	-0.47	-0.35	-0.41	-0.32	-0.19	-0.51	-0.62	-0.50	-0.63	-0.60	-0.54	-0.68	-0.66	-0.77	-0.82	-0.81
		500	500	0.34	0.19	0.00	0.01	0.03	0.08	-0.45	0.02	-0.02	0.00	-0.38	0.05	0.37	0.34	0.45	-0.50	-0.48	-0.49	-0.47	-0.56
		1000	500	0.13	0.07	0.03	0.02	0.05	0.02	0.03	-0.03	-0.02	0.02	0.02	0.08	0.19	0.02	0.09	-0.36	-0.15	0.09	0.19	0.20
	60/40	200	471	0.89	1.11	-0.58	-0.66	-0.57	-0.51	-0.47	-0.50	-0.51	-0.65	-0.54	-0.53	-0.51	-0.48	-0.43	-0.64	-0.65	-0.83	-0.80	-0.84
		500	499	1.37	3.73	0.27	0.13	0.17	0.61	0.23	0.11	0.10	0.10	-0.33	0.50	0.92	1.19	0.41	0.20	-0.07	-0.43	-0.31	0.58
		1000	500	0.48	0.40	0.04	0.04	0.11	0.02	0.03	-0.03	0.00	0.03	0.02	0.05	0.29	0.12	0.09	-0.18	0.38	-0.12	0.13	0.07
	80/20	200	424	0.35	0.83	-0.54	-0.56	-0.54	-0.32	-0.37	-0.50	-0.45	-0.66	-0.43	-0.53	-0.61	-0.63	-0.10	-0.65	-0.68	-0.83	-0.80	-0.78
		500	495	0.70	0.87	0.03	0.02	0.10	0.12	0.06	0.03	0.04	0.01	-0.38	0.15	0.24	0.26	0.18	-0.55	-0.56	-0.73	-0.63	-0.59
		1000	500	0.62	0.34	0.03	0.04	0.11	0.05	0.05	-0.02	0.00	0.04	-0.01	0.08	0.75	0.85	0.57	-0.43	-0.19	-0.22	0.13	-0.10

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.9a. Item Response Standard Error Recovery: Poorly-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	263	60.30	0.19	-0.72	1.57	-0.24	-0.33	-0.60	-0.65	-0.64	-0.56	-0.57	-0.01	-0.54	-0.75	-0.15	--	--	--	--	--
		500	423	-0.28	0.23	-0.32	0.30	0.24	0.18	-0.56	0.38	0.39	0.21	-0.36	0.52	-0.43	-0.48	-0.50	--	--	--	--	--
		1000	480	-0.34	0.98	0.71	1.63	1.30	3.83	4.62	6.91	4.63	0.57	0.83	5.25	4.13	-0.07	1.53	--	--	--	--	--
	60/40	200	111	-0.61	0.38	-0.60	0.24	0.02	0.31	-0.75	0.09	-0.37	-0.68	-0.64	0.69	-0.69	-0.86	-0.60	--	--	--	--	--
		500	182	-0.63	0.07	-0.82	0.25	0.06	0.08	-0.76	0.12	0.24	0.16	-0.07	0.29	-0.67	-0.63	0.34	--	--	--	--	--
		1000	284	-0.53	0.11	-0.01	0.19	0.18	0.14	-0.68	0.26	0.22	-0.06	-0.24	0.21	-0.76	-0.48	0.59	--	--	--	--	--
	80/20	200	432	-0.68	0.08	-0.56	0.19	0.09	-0.32	-0.82	0.15	-0.66	-0.73	0.36	-0.30	-0.60	-0.38	0.06	--	--	--	--	--
		500	480	-0.48	0.11	0.20	0.06	0.06	0.01	-0.55	0.10	0.24	0.08	-0.40	0.21	0.46	-0.25	0.32	--	--	--	--	--
		1000	484	-0.45	0.05	0.16	0.12	0.02	0.02	-0.25	0.05	0.07	0.03	0.18	0.16	0.34	-0.53	0.19	--	--	--	--	--
Unordered	50/50	200	243	-0.55	0.14	-0.77	0.10	-0.08	-0.53	-0.83	-0.02	-0.55	-0.65	-0.54	-0.51	-0.66	-0.82	-0.75	--	--	--	--	--
		500	366	1.37	0.40	-0.61	1.27	0.74	0.76	17.82	0.80	1.27	1.38	0.10	2.26	-0.60	2.14	0.03	--	--	--	--	--
		1000	459	4.90	1.36	-0.63	0.54	0.33	0.59	1.04	0.46	0.41	0.85	2.53	1.54	0.72	-0.23	1.97	--	--	--	--	--
	60/40	200	102	-0.57	-0.01	-0.70	0.04	-0.01	-0.42	-0.81	-0.30	-0.61	-0.79	-0.57	-0.68	-0.88	-0.89	-0.82	--	--	--	--	--
		500	105	-0.52	0.02	-0.83	0.13	-0.10	0.00	-0.79	0.30	0.10	0.44	-0.68	0.11	-0.67	-0.30	0.05	--	--	--	--	--
		1000	155	1.02	4.14	3.72	13.04	5.74	3.46	1.07	3.37	3.88	4.86	13.21	1.43	3.05	1.23	2.18	--	--	--	--	--
	80/20	200	437	-0.70	0.30	-0.54	0.41	0.31	-0.50	-0.75	0.05	-0.71	-0.68	-0.17	-0.19	-0.58	-0.75	0.00	--	--	--	--	--
		500	489	-0.36	0.24	0.27	0.17	0.24	0.13	-0.45	0.30	0.28	0.14	0.52	0.32	0.47	-0.35	0.31	--	--	--	--	--
		1000	486	0.05	0.06	0.27	0.21	0.14	0.01	-0.47	0.06	0.10	0.14	0.52	0.19	0.92	-0.50	0.48	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.9b. Item Response Standard Error Recovery: Poorly-Defined Classes with Moderate Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.95	0.50	0.50	0.40	0.30	0.30	0.05	0.40	0.50	0.73	0.21	0.40	0.40	0.02	0.50	0.50	0.40	0.05	0.21	0.21
Ordered	50/50	200	258	-0.83	0.09	-0.61	0.08	0.08	-0.06	-0.66	0.04	0.42	-0.75	-0.74	-0.61	-0.41	-0.76	-0.73	-0.78	-0.73	-0.64	-0.66	-0.73
		500	403	-0.52	0.32	-0.42	0.34	0.38	0.13	-0.69	0.12	0.32	0.34	-0.18	0.37	-0.65	-0.51	0.42	-0.48	-0.43	-0.33	-0.20	-0.58
		1000	454	-0.47	0.03	0.37	0.16	0.12	0.00	-0.50	0.04	0.09	0.04	0.21	0.18	0.46	-0.66	0.26	0.28	0.20	-0.25	0.21	-0.37
	60/40	200	195	-0.74	0.20	-0.72	0.12	0.05	0.05	-0.82	0.24	-0.31	-0.53	-0.59	-0.23	-0.64	-0.90	-0.30	-0.06	-0.58	-0.81	-0.74	-0.76
		500	332	-0.56	0.49	-0.67	0.46	0.53	0.08	-0.66	0.25	0.33	0.58	-0.28	0.73	-0.61	-0.58	0.39	-0.42	-0.27	-0.12	-0.52	-0.54
		1000	444	-0.45	0.22	0.07	0.32	0.13	0.15	-0.47	0.13	0.14	0.29	0.52	0.15	-0.46	-0.49	0.41	-0.50	-0.33	-0.25	-0.07	-0.13
	80/20	200	112	-0.83	-0.06	-0.74	0.08	-0.03	-0.06	-0.89	-0.26	-0.66	-0.85	-0.63	-0.62	-0.82	-0.91	-0.18	-0.75	-0.70	-0.75	-0.70	-0.69
		500	143	-0.51	0.03	0.10	0.19	0.04	-0.11	-0.76	-0.03	0.08	-0.13	0.38	0.09	-0.80	-0.34	0.06	-0.66	-0.80	-0.49	-0.59	-0.69
		1000	218	-0.48	0.08	-0.52	0.16	0.17	0.19	-0.48	0.12	0.09	0.14	-0.52	0.40	-0.72	-0.36	0.53	-0.52	-0.62	-0.52	-0.41	-0.50
Unordered	50/50	200	261	-0.65	0.22	-0.35	0.30	-0.59	-0.51	-0.82	0.23	-0.70	-0.75	-0.55	-0.11	-0.75	-0.76	-0.24	-0.59	-0.63	-0.61	-0.69	-0.69
		500	421	-0.63	0.32	-0.49	0.40	0.43	0.32	-0.27	0.26	0.52	0.44	-0.36	0.04	-0.61	-0.54	0.08	-0.44	-0.22	-0.19	0.24	-0.20
		1000	477	1.49	0.14	0.09	0.25	0.14	0.10	-0.52	0.14	0.14	0.13	0.22	0.17	0.51	-0.55	0.38	0.23	0.19	-0.31	-0.03	-0.29
	60/40	200	191	0.10	1.31	-0.37	2.02	1.07	0.17	-0.84	0.90	-0.37	-0.37	-0.53	1.09	-0.49	-0.77	-0.59	0.87	1.58	-0.73	-0.19	-0.47
		500	336	4.44	0.34	-0.30	0.23	0.34	0.29	-0.49	0.35	0.48	-0.25	-0.42	-0.27	-0.14	0.69	-0.25	-0.50	1.42	-0.30	-0.51	-0.53
		1000	451	10.99	3.01	3.47	0.37	4.89	0.52	1.43	2.80	1.61	7.84	1.14	5.18	4.08	-0.49	6.55	3.04	6.59	6.68	0.35	0.16
	80/20	200	131	-0.77	-0.77	-0.84	0.04	0.10	-0.73	-0.76	0.02	-0.64	-0.68	-0.71	-0.62	-0.82	-0.93	-0.73	-0.57	-0.74	-0.66	-0.55	-0.41
		500	142	-0.65	0.65	-0.35	0.89	0.44	0.68	-0.81	0.81	0.72	0.15	-0.26	1.23	-0.48	-0.75	2.27	-0.20	-0.33	-0.61	-0.45	0.50
		1000	217	-0.04	1.46	0.09	1.70	2.51	4.26	0.66	10.21	2.25	5.27	-0.26	0.82	-0.49	0.22	1.12	2.52	2.10	0.48	0.05	0.53

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.10a. Item Response Standard Error Recovery: Poorly-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance Pattern A

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05	N/A	N/A	N/A	N/A	N/A
Ordered	50/50	200	298	0.18	-0.91	0.17	-0.46	-0.13	1.60	-0.06	0.60	0.00	-0.30	-0.63	-0.38	-0.43	1.09	0.04	--	--	--	--	--
		500	386	0.21	-0.84	0.04	0.07	0.06	0.75	0.08	0.25	0.43	-0.55	-0.83	0.23	1.11	1.21	1.04	--	--	--	--	--
		1000	428	0.10	-0.71	0.02	0.09	0.13	0.14	0.07	0.07	0.01	-0.16	-0.78	0.12	0.44	0.33	0.44	--	--	--	--	--
	60/40	200	301	0.27	-0.71	0.05	-0.44	-0.41	0.58	-0.37	0.85	-0.44	-0.57	-0.67	-0.45	-0.54	-0.42	0.13	--	--	--	--	--
		500	352	0.11	-0.78	0.01	0.19	0.07	1.78	0.48	0.60	0.63	4.05	-0.14	0.43	2.95	0.90	3.24	--	--	--	--	--
		1000	429	0.07	-0.73	0.05	0.13	0.06	0.13	0.11	0.12	0.07	0.06	-0.80	0.07	0.31	0.27	0.30	--	--	--	--	--
	80/20	200	330	0.07	-0.89	0.07	0.07	-0.49	0.51	0.40	0.52	0.36	0.58	0.00	0.55	0.84	0.53	0.10	--	--	--	--	--
		500	411	-0.01	-0.88	0.05	0.05	0.09	0.27	0.10	0.24	0.11	-0.59	-0.41	0.37	0.63	0.51	1.18	--	--	--	--	--
		1000	432	0.05	-0.68	0.02	0.03	0.05	0.09	0.06	0.00	0.00	-0.79	-0.83	0.05	0.10	0.06	0.12	--	--	--	--	--
Unordered	50/50	200	299	0.42	-0.89	0.15	-0.47	-0.48	1.74	-0.33	0.58	0.75	-0.78	-0.61	-0.25	-0.23	1.67	0.57	--	--	--	--	--
		500	397	0.08	-0.56	0.26	0.11	0.17	0.53	0.20	0.38	0.39	1.88	-0.60	0.41	1.07	0.96	0.83	--	--	--	--	--
		1000	454	0.04	-0.85	0.10	0.09	0.13	0.59	0.28	0.26	0.19	-0.63	-0.75	0.17	0.71	0.24	0.84	--	--	--	--	--
	60/40	200	310	0.17	-0.93	0.18	-0.49	-0.47	0.78	-0.41	0.41	-0.61	-0.24	-0.75	0.16	-0.60	-0.51	-0.42	--	--	--	--	--
		500	383	1.22	-0.51	1.15	0.49	0.47	10.47	8.42	19.01	7.99	0.33	0.16	12.69	28.03	10.97	26.01	--	--	--	--	--
		1000	444	0.04	-0.82	0.08	0.10	0.08	0.12	0.16	0.04	0.10	-0.30	-0.79	0.01	0.17	0.16	0.13	--	--	--	--	--
	80/20	200	331	0.20	-0.84	0.02	-0.04	-0.02	0.58	0.16	0.32	0.25	0.45	-0.83	0.88	0.21	1.71	1.00	--	--	--	--	--
		500	413	0.04	-0.89	0.06	0.04	0.07	0.46	0.12	0.26	0.07	-0.28	-0.83	0.31	0.42	0.25	0.80	--	--	--	--	--
		1000	456	0.02	-0.82	0.04	0.02	0.04	0.07	0.05	0.04	0.00	-0.75	-0.83	0.05	0.08	0.04	0.16	--	--	--	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.10b. Item Response Standard Error Recovery: Poorly-Defined Classes with High Thresholds, Four-Class Solutions, Non-Invariance Pattern B

Transition Pattern	Class Prevalence Split	Total Sample Size	Number Valid Reps	Relative Bias in Estimated Time 1 Item Response Logit Standard Errors																			
				Class 1 Item Population Probabilities					Class 2 Item Population Probabilities					Class 3 Item Population Probabilities					Class 4 Item Population Probabilities				
				0.92	0.99	0.73	0.08	0.08	0.18	0.18	0.50	0.73	0.99	0.01	0.18	0.27	0.73	0.05	0.82	0.01	0.99	0.01	0.01
Ordered	50/50	200	485	2.08	1.19	0.76	-0.14	1.08	3.76	0.72	3.62	2.70	2.78	-0.89	0.89	3.91	3.43	5.09	5.27	0.28	-0.83	-0.85	0.64
		500	498	0.80	-0.26	0.44	0.53	0.47	8.11	1.72	5.04	2.21	3.94	-0.46	1.87	7.75	6.34	14.32	10.60	1.23	-0.70	-0.81	0.73
		1000	499	0.83	0.02	0.23	0.32	0.35	3.56	0.64	2.43	0.69	4.15	-0.47	0.73	4.58	1.60	4.97	5.71	0.02	-0.80	-0.63	-0.54
	60/40	200	486	0.95	-0.86	0.39	0.30	0.55	2.99	0.89	2.39	1.36	7.07	-0.85	0.45	3.26	2.38	5.54	2.12	0.45	-0.93	-0.72	0.17
		500	496	1.60	-0.31	0.80	0.62	0.64	7.75	5.13	6.07	3.96	6.22	-0.46	5.58	19.41	12.13	16.46	39.45	0.84	-0.92	1.06	0.01
		1000	498	0.27	-0.55	0.14	0.14	0.11	2.10	0.43	1.47	0.67	0.21	-0.76	0.38	2.88	2.53	3.65	4.86	0.47	-0.65	-0.67	-0.44
	80/20	200	457	1.65	-0.63	0.89	-0.18	0.52	5.14	0.08	3.54	2.63	0.94	-0.89	0.57	0.37	3.34	4.80	12.60	0.53	-0.88	-0.90	9.82
		500	496	0.54	0.12	0.42	0.36	0.55	2.83	0.65	2.66	1.33	1.58	-0.84	1.12	4.60	4.02	5.41	3.09	0.74	1.28	-0.85	0.14
		1000	498	0.22	0.04	0.09	0.14	0.08	1.89	0.23	1.51	0.42	0.64	-0.72	0.43	3.41	2.87	3.46	5.99	-0.28	-0.77	-0.70	-0.48
Unordered	50/50	200	487	1.23	-0.56	0.71	-0.01	0.48	7.70	0.92	6.88	5.95	4.59	-0.83	3.94	4.94	6.92	14.44	6.84	2.14	-0.90	-0.85	-0.13
		500	498	0.70	-0.46	0.60	0.45	0.33	4.01	1.07	2.45	2.12	0.66	-0.82	0.92	2.97	2.46	5.78	4.31	2.30	-0.82	-0.48	1.03
		1000	497	0.19	0.08	3.26	1.39	0.93	2.64	2.54	11.05	9.24	0.38	-0.65	9.07	40.24	35.09	12.25	41.67	4.14	-0.77	-0.77	-0.56
	60/40	200	485	3.69	-0.57	1.49	1.37	0.23	6.81	4.74	6.12	2.12	3.52	-0.09	3.79	6.24	3.40	6.00	5.43	4.36	-0.86	-0.68	1.42
		500	497	3.03	-0.28	1.30	0.76	0.80	16.12	2.56	12.83	5.57	6.31	-0.72	5.20	14.34	9.83	40.71	18.44	8.23	-0.65	-0.44	0.03
		1000	498	0.46	-0.43	0.57	0.35	0.23	3.29	0.74	2.66	1.00	0.25	-0.65	0.68	2.94	2.21	4.26	3.99	0.41	-0.68	-0.74	-0.21
	80/20	200	467	2.59	-0.72	1.16	0.29	0.01	6.95	0.52	3.46	2.14	1.57	-0.89	4.50	3.42	0.86	5.69	9.77	3.33	-0.84	-0.81	5.40
		500	493	4.52	-0.51	1.59	2.01	1.84	5.83	2.32	7.16	4.83	3.35	-0.63	2.35	14.64	15.01	11.33	23.95	5.46	-0.39	-0.10	0.37
		1000	498	0.54	-0.67	0.38	0.26	0.15	3.13	0.67	2.20	1.30	0.90	-0.68	1.19	4.66	4.31	5.38	4.74	2.15	-0.77	-0.74	2.52

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.11a. Latent Class Prevalence Standard Error Recovery: LMI Pattern A, Three-Class Solutions

Relative Bias in Estimated Class Prevalence Standard Errors								
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern		Number Valid Reps	Unordered Transition Pattern	
				C1#1	C1#2		C1#1	C1#2
Well-Defined, Low Thresholds	50/50	200	339	0.48	0.61	374	0.28	0.39
		500	392	0.15	0.28	433	0.20	0.22
		1000	446	0.14	0.09	479	0.12	0.60
	60/40	200	460	0.21	0.41	471	0.25	2.67
		500	493	0.22	0.15	494	0.26	0.24
		1000	498	0.15	0.09	491	0.11	0.11
	80/20	200	93	0.35	0.21	140	0.52	0.44
		500	77	0.13	0.07	143	0.27	0.07
		1000	63	0.09	0.00	143	0.19	0.09
Well-Defined, Moderate Thresholds	50/50	200	465	0.24	0.05	485	0.06	0.00
		500	487	0.08	0.03	500	0.04	0.01
		1000	499	0.06	-0.08	500	0.06	-0.05
	60/40	200	500	0.10	0.16	500	0.07	0.32
		500	500	0.05	0.08	500	0.04	0.03
		1000	500	0.07	0.03	500	0.06	-0.01
	80/20	200	174	0.27	0.07	218	0.20	0.02
		500	138	0.17	0.32	219	0.11	0.03
		1000	102	0.14	0.11	186	0.07	0.00
Well-Defined, High Thresholds	50/50	200	488	0.25	0.21	497	0.04	-0.02
		500	499	0.04	-0.05	500	0.02	-0.04
		1000	500	0.05	-0.04	500	0.05	-0.05
	60/40	200	500	0.12	0.18	500	0.05	0.00
		500	500	0.03	-0.01	500	0.02	-0.03
		1000	500	0.05	-0.04	500	0.05	-0.05
	80/20	200	197	0.45	0.43	260	0.22	0.15
		500	159	0.64	0.67	244	0.12	0.07
		1000	123	0.17	0.10	247	0.10	0.02
Poorly-Defined, Moderate Thresholds	50/50	200	471	1.30	0.44	473	0.43	0.43
		500	496	0.19	0.40	499	0.18	0.20
		1000	498	0.09	0.16	500	0.05	0.09
	60/40	200	492	0.81	1.79	496	0.45	0.33
		500	500	0.47	0.33	498	0.11	0.28
		1000	500	0.06	0.11	499	0.02	0.09
	80/20	200	203	0.47	0.29	253	0.91	0.13
		500	214	0.16	1.13	305	0.23	0.41
		1000	221	0.28	0.33	353	0.28	0.38
Poorly-Defined High Thresholds	50/50	200	0	--	--	0	--	--
		500	0	--	--	0	--	--
		1000	0	--	--	0	--	--
	60/40	200	48	0.33	0.07	267	0.45	0.00
		500	2	0.27	-0.28	167	0.03	0.63
		1000	0	--	--	116	0.04	0.29
	80/20	200	0	--	--	0	--	--
		500	0	--	--	0	--	--
		1000	0	--	--	0	--	--

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.11b. Latent Class Prevalence Standard Error Recovery: LMI Pattern B, Three-Class Solutions

Relative Bias in Estimated Class Prevalence Standard Errors								
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern		Number Valid Reps	Unordered Transition Pattern	
				C1#1	C1#2		C1#1	C1#2
Well-Defined, Low Thresholds	50/50	200	370	0.65	0.54	350	0.57	0.65
		500	431	0.46	0.35	385	0.37	0.60
		1000	461	0.19	0.19	436	0.28	0.74
	60/40	200	428	1.12	2.84	400	1.18	0.45
		500	464	0.39	0.49	451	0.28	0.22
		1000	483	0.12	0.13	472	0.07	0.11
	80/20	200	468	1.41	1.09	459	0.30	0.46
		500	491	0.15	0.45	490	0.28	0.15
		1000	477	0.08	0.09	484	0.10	0.14
Well-Defined, Moderate Thresholds	50/50	200	491	-0.17	0.24	473	-0.21	0.07
		500	499	-0.19	0.24	495	-0.33	0.01
		1000	500	-0.31	0.18	500	-0.43	0.01
	60/40	200	497	-0.04	0.13	489	-0.04	0.05
		500	500	-0.11	0.08	500	-0.14	0.01
		1000	500	-0.13	0.22	500	-0.20	-0.01
	80/20	200	500	0.20	0.46	500	0.07	0.06
		500	500	0.15	0.10	500	0.07	0.03
		1000	500	0.21	0.44	500	0.06	0.00
Well-Defined, High Thresholds	50/50	200	497	-0.37	0.12	491	-0.41	-0.01
		500	500	-0.27	0.04	500	-0.48	-0.02
		1000	500	-0.30	0.00	500	-0.29	-0.04
	60/40	200	500	-0.35	0.08	499	-0.36	0.03
		500	500	-0.40	0.11	500	-0.42	-0.03
		1000	500	-0.27	0.20	500	-0.28	-0.04
	80/20	200	500	-0.12	1.01	500	-0.16	-0.01
		500	500	-0.24	0.02	500	-0.24	-0.02
		1000	500	-0.33	-0.01	500	-0.34	-0.04
Poorly-Defined, Moderate Thresholds	50/50	200	485	0.54	0.33	473	0.51	0.58
		500	499	0.30	0.38	498	0.29	0.16
		1000	500	0.09	0.12	500	0.03	0.09
	60/40	200	491	3.81	1.15	476	9.19	2.43
		500	499	0.97	0.55	499	0.21	0.15
		1000	500	0.29	0.49	498	0.02	0.07
	80/20	200	497	1.01	0.42	490	0.53	0.57
		500	499	0.13	0.26	500	0.07	0.12
		1000	500	0.12	0.16	499	0.16	0.13
Poorly-Defined High Thresholds	50/50	200	0	--	--	--	--	--
		500	0	--	--	--	--	--
		1000	0	--	--	--	--	--
	60/40	200	4	0.44	0.54	3	3.95	0.39
		500	0	--	--	--	--	--
		1000	0	--	--	--	--	--
	80/20	200	161	0.15	0.99	137	0.05	0.23
		500	60	-0.01	0.27	42	0.28	1.79
		1000	18	0.62	0.26	10	0.41	0.39

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.12a. Latent Class Prevalence Standard Error Recovery: LMI Pattern A, Four-Class Solutions

Relative Bias in Estimated Class Prevalence Standard Errors										
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern			Number Valid Reps	Unordered Transition Pattern		
				C1#1	C1#2	C1#3		C1#1	C1#2	C1#3
Well-Defined, Low Thresholds	50/50	200	368	0.51	0.28	0.44	313	0.34	0.37	0.24
		500	468	1.15	0.26	1.12	439	0.95	0.95	1.08
		1000	474	0.43	0.52	0.69	483	0.26	0.16	0.10
	60/40	200	185	0.13	0.02	-0.03	115	0.11	0.01	-0.15
		500	283	0.34	0.21	0.14	137	0.30	0.16	0.05
		1000	387	0.46	0.15	0.17	233	0.37	0.49	0.92
	80/20	200	434	2.05	0.51	2.26	432	0.01	0.14	0.41
		500	468	0.23	0.25	0.32	468	0.33	0.28	0.36
		1000	473	0.30	0.32	0.55	477	0.22	0.75	0.25
Well-Defined, Moderate Thresholds	50/50	200	410	0.79	0.87	2.10	423	2.16	1.93	0.80
		500	458	0.82	0.10	0.38	470	2.20	1.82	1.65
		1000	478	0.13	0.01	0.05	492	0.11	-0.02	0.02
	60/40	200	415	0.93	1.51	1.74	365	0.39	0.17	0.32
		500	446	0.65	0.47	0.46	475	3.30	2.60	2.75
		1000	470	0.29	0.57	0.51	488	0.11	-0.01	0.05
	80/20	200	388	0.56	0.43	0.79	402	0.57	0.28	0.38
		500	441	0.18	0.10	0.09	467	0.14	0.07	0.08
		1000	474	0.25	0.06	0.12	479	0.14	-0.01	0.04
Well-Defined, High Thresholds	50/50	200	289	3.79	3.21	2.12	313	9.96	5.79	4.94
		500	403	0.69	0.44	0.79	432	79.64	68.07	77.99
		1000	441	0.20	0.03	0.19	476	149.57	123.15	135.91
	60/40	200	290	0.64	2.08	2.93	345	5852.36	5723.96	5752.56
		500	398	2.54	1.82	2.17	430	1585.93	1569.47	1629.60
		1000	451	0.54	0.47	0.58	479	6258.40	5934.85	5784.87
	80/20	200	324	1.14	1.02	1.67	312	0.76	0.38	1.82
		500	389	0.40	0.21	0.31	413	0.63	0.43	0.41
		1000	419	0.15	0.05	0.15	447	0.25	0.07	0.15
Poorly-Defined, Moderate Thresholds	50/50	200	271	1.10	-0.05	0.80	242	0.25	0.19	0.01
		500	421	0.76	0.51	0.55	357	1.53	4.25	2.90
		1000	480	2.95	7.59	6.03	457	2.08	2.40	1.63
	60/40	200	121	0.73	0.69	-0.01	106	0.25	0.03	-0.03
		500	171	0.20	0.34	0.64	95	0.18	0.20	-0.09
		1000	275	0.71	1.19	1.59	156	4.95	13.24	8.23
	80/20	200	440	0.22	0.14	0.31	442	0.92	0.10	0.89
		500	480	0.21	0.25	0.47	489	0.38	0.28	0.39
		1000	484	0.15	0.21	0.45	486	0.76	0.20	0.49
Poorly-Defined High Thresholds	50/50	200	298	0.77	1.85	2.18	299	0.85	2.94	3.19
		500	386	0.61	1.31	2.14	397	10.41	4.93	5.07
		1000	428	0.33	0.47	0.43	454	2.28	2.13	2.13
	60/40	200	301	0.81	1.83	2.03	311	3.74	1.79	1.44
		500	352	0.70	7.59	6.12	388	4.13	82.67	101.96
		1000	429	0.25	0.31	0.40	445	0.30	0.11	0.21
	80/20	200	330	0.47	3.05	3.42	331	3.35	4.50	1.85
		500	411	0.70	1.89	1.15	413	0.09	1.13	1.26
		1000	432	0.09	0.21	0.34	456	0.04	0.21	0.28

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.12b. Latent Class Prevalence Standard Error Recovery: LMI Pattern B, Four-Class Solutions

Relative Bias in Estimated Class Prevalence Standard Errors										
Class Separation Level	Class Prevalence Split	Total Sample Size	Number Valid Reps	Ordered Transition Pattern			Number Valid Reps	Unordered Transition Pattern		
				C1#1	C1#2	C1#3		C1#1	C1#2	C1#3
Well-Defined, Low Thresholds	50/50	200	348	3.43	4.25	2.51	364	2.21	0.36	0.33
		500	451	0.73	0.32	0.47	474	0.48	0.05	0.16
		1000	469	0.50	0.12	0.36	492	0.23	0.12	0.14
	60/40	200	303	0.04	0.06	0.04	319	0.25	0.45	0.42
		500	427	2.06	0.24	1.04	457	0.33	0.06	0.15
		1000	470	0.35	0.12	0.13	488	1.12	0.58	0.37
	80/20	200	155	0.42	0.06	-0.08	159	0.04	0.06	-0.07
		500	236	0.30	0.05	0.10	238	1.32	1.18	1.12
		1000	372	0.44	0.17	0.31	366	0.71	0.05	0.32
Well-Defined, Moderate Thresholds	50/50	200	489	0.86	1.65	2.25	495	0.95	1.09	2.78
		500	482	0.25	0.33	1.15	494	0.12	0.10	0.22
		1000	484	0.25	0.65	0.62	498	0.08	0.26	0.23
	60/40	200	487	0.73	1.34	2.44	492	0.60	1.16	1.43
		500	480	0.13	0.24	0.47	496	0.12	0.06	0.24
		1000	478	0.98	3.83	11.25	500	0.10	0.01	0.20
	80/20	200	459	2.14	2.70	2.30	456	1.23	1.07	1.40
		500	485	0.76	0.53	2.18	494	0.79	0.34	0.94
		1000	492	1.48	0.42	0.86	495	0.12	0.02	0.18
Well-Defined, High Thresholds	50/50	200	445	26.76	82.09	145.68	486	12.77	13.68	38.41
		500	499	2.57	7.73	20.52	500	0.46	0.49	1.63
		1000	498	1.08	1.60	6.21	500	0.10	-0.01	0.04
	60/40	200	432	33.21	143.84	127.49	471	21.92	24.97	41.68
		500	499	2.74	10.65	23.15	499	1.30	0.60	1.71
		1000	498	0.95	1.42	5.77	500	0.18	-0.01	0.07
	80/20	200	379	18.39	78.33	103.40	424	12.83	16.47	28.64
		500	494	6.46	16.63	25.58	495	3.78	2.90	3.95
		1000	498	1.05	4.62	6.60	500	0.25	0.08	0.22
Poorly-Defined, Moderate Thresholds	50/50	200	266	0.01	0.06	0.04	270	1.67	0.32	0.04
		500	401	0.51	0.37	0.43	425	0.46	0.41	0.97
		1000	454	0.40	0.13	0.39	476	0.49	0.19	0.44
	60/40	200	201	0.13	0.22	0.31	207	0.22	0.21	0.53
		500	329	0.75	0.50	0.54	335	0.91	0.68	0.49
		1000	440	0.63	0.42	0.62	451	2.81	3.29	3.25
	80/20	200	118	-0.11	-0.05	0.01	131	0.08	0.05	0.15
		500	136	0.16	0.17	-0.01	132	0.76	0.90	1.92
		1000	208	0.52	0.43	1.00	205	7.49	11.32	1.94
Poorly-Defined High Thresholds	50/50	200	485	20.88	14.08	14.57	486	4.04	12.15	14.30
		500	498	7.52	22.18	20.58	498	2.46	6.26	6.91
		1000	499	1.50	8.11	9.19	497	6.03	5.46	6.25
	60/40	200	486	13.36	12.82	10.77	485	7.85	11.96	13.12
		500	496	2.63	26.17	30.12	497	4.14	27.48	30.47
		1000	498	0.81	5.14	5.77	498	1.93	5.65	6.14
	80/20	200	463	17.30	13.75	9.30	472	10.30	13.44	14.31
		500	496	2.08	5.89	6.12	495	7.84	10.13	14.70
		1000	498	0.75	3.70	4.27	498	1.43	5.55	6.09

Note. Bolded cells indicate instances where the absolute value of the relative bias is greater than or equal to 0.10, a recommended maximum for acceptable magnitudes of bias. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.13a. Transition Probability Standard Error Recovery: LMI Pattern A, Three-Class Solutions

Absolute Bias in Estimated Transition Matrix Standard Errors														
Class Separation Level	Class Prevalence Split	Total Sample Size	Ordered Transition Pattern						Unordered Transition Pattern					
			C2#1 on C1#1	C2#2 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#1 on C1#1	C2#2 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#1 on C1#3	C2#2 on C1#3
Well-Defined, Low Thresholds	50/50	200	0.45	0.50	0.75	0.69	0.75	3.00	0.32	0.54	0.78	0.66	0.38	1.19
		500	0.14	0.24	0.33	0.23	0.15	2.46	0.16	0.23	0.40	0.33	0.16	1.07
		1000	0.20	0.23	0.19	0.37	0.24	4.93	0.58	0.90	0.23	0.40	0.23	1.25
	60/40	200	0.37	0.53	1.00	0.55	0.75	1.19	0.57	9.71	0.85	6.68	0.97	2.60
		500	0.15	0.28	0.60	0.34	0.33	1.20	0.41	0.46	1.01	0.56	0.50	0.62
		1000	0.12	0.10	0.30	0.37	0.16	1.71	0.08	0.15	0.33	0.42	0.26	1.19
	80/20	200	0.33	0.21	0.70	0.02	0.22	2.74	0.47	0.59	1.05	0.64	0.36	1.38
		500	0.10	0.18	0.30	0.25	-0.04	7.39	0.14	0.34	0.11	0.21	-0.06	2.74
		1000	-0.02	0.01	0.02	0.05	0.02	17.40	0.08	0.10	0.09	0.20	0.05	1.16
Well-Defined, Moderate Thresholds	50/50	200	0.13	0.01	2.19	0.19	-0.45	3.30	0.02	-0.01	0.30	0.20	-0.32	0.52
		500	0.00	0.01	0.58	0.14	-0.66	2.17	-0.02	-0.01	0.00	-0.01	-0.47	0.46
		1000	-0.03	0.00	0.01	-0.02	-0.74	2.68	-0.04	0.00	-0.05	0.01	-0.44	0.04
	60/40	200	0.10	0.03	1.36	0.57	-0.01	2.74	0.04	0.03	1.27	0.47	0.51	0.46
		500	-0.02	-0.01	0.86	0.11	0.04	2.45	-0.03	-0.02	0.01	-0.03	-0.04	0.10
		1000	-0.03	0.00	0.33	0.03	-0.04	1.94	-0.03	-0.01	-0.03	0.01	0.01	0.03
	80/20	200	-0.02	-0.04	0.42	0.15	-0.57	4.69	-0.02	-0.01	0.50	0.29	-0.52	0.20
		500	0.09	0.14	0.43	0.11	-0.68	3.71	0.02	0.05	-0.01	0.00	-0.65	0.11
		1000	0.05	0.08	0.05	0.03	0.84	3.03	0.03	0.04	-0.03	-0.01	0.05	0.06
Well-Defined, High Thresholds	50/50	200	0.26	0.06	5.06	2.17	-0.47	14.36	0.06	0.00	0.21	0.10	-0.54	0.32
		500	-0.02	-0.03	0.12	0.04	-0.65	10.96	-0.03	-0.03	-0.03	-0.06	-0.55	0.00
		1000	-0.03	-0.01	-0.06	0.06	-0.57	18.03	-0.03	-0.02	-0.04	0.02	-0.19	-0.02
	60/40	200	0.15	0.03	2.74	0.62	0.42	16.86	0.06	0.00	0.48	0.19	0.06	0.11
		500	-0.01	-0.02	0.62	0.26	-0.67	8.44	-0.02	-0.03	-0.06	-0.05	-0.24	0.00
		1000	-0.03	-0.01	0.02	0.12	-0.76	4.70	-0.03	-0.02	-0.06	0.02	-0.16	-0.02
	80/20	200	0.69	0.10	1.81	0.75	-0.29	25.85	0.16	0.01	0.77	0.39	-0.41	0.18
		500	0.23	0.10	11.37	3.39	3.43	5.74	0.01	0.00	0.01	0.04	0.23	0.05
		1000	0.03	0.06	0.00	0.06	3.83	6.57	-0.01	0.02	-0.01	0.07	0.13	0.03
Poorly-Defined, Moderate Thresholds	50/50	200	0.90	0.41	3.51	0.68	1.70	1.70	0.48	0.45	2.04	0.68	0.67	0.79
		500	0.32	0.28	1.15	1.39	0.31	1.49	0.35	0.54	0.66	0.22	0.22	0.56
		1000	0.25	0.13	1.23	0.56	0.12	3.08	0.09	0.06	0.44	0.17	0.04	0.32
	60/40	200	0.66	1.56	6.56	1.19	5.89	2.23	0.46	0.47	1.24	0.72	0.72	0.67
		500	0.81	0.66	1.32	0.29	0.93	1.85	0.20	0.13	0.65	0.30	0.62	0.45
		1000	0.16	0.24	2.28	0.39	0.46	1.80	0.06	0.05	0.37	0.11	0.16	0.27
	80/20	200	0.39	0.35	1.59	2.09	0.11	0.90	0.27	0.23	1.57	0.46	0.45	0.16
		500	0.60	0.30	0.91	7.35	-0.02	1.20	0.43	0.52	0.98	0.37	0.16	0.71
		1000	0.48	0.29	1.65	0.41	0.30	2.74	0.63	0.20	0.68	0.28	0.29	0.96
Poorly-Defined High Thresholds	50/50	200	--	--	--	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--	--	--	--
	60/40	200	0.16	0.15	3.53	0.18	1.79	1.03	0.15	0.22	0.58	0.36	0.84	0.90
		500	-0.41	0.03	-1.00	-0.62	-0.83	-1.00	0.04	0.16	1.71	1.86	0.26	2.16
		1000	--	--	--	--	--	--	-0.08	0.10	0.27	0.39	-0.06	1.63
	80/20	200	--	--	--	--	--	--	--	--	--	--	--	--
		500	--	--	--	--	--	--	--	--	--	--	--	--
		1000	--	--	--	--	--	--	--	--	--	--	--	--

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table B.13b. Transition Probability Standard Error Recovery: LMI Pattern B, Three-Class Solutions

Absolute Bias in Estimated Transition Matrix Standard Errors														
Class Separation Level	Class Prevalence Split	Total Sample Size	Ordered Transition Pattern						Unordered Transition Pattern					
			C2#1 on C1#1	C2#2 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#1 on C1#1	C2#2 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#1 on C1#3	C2#2 on C1#3
Well-Defined, Low Thresholds	50/50	200	0.60	0.72	1.36	1.91	7.08	2.33	0.50	1.06	0.79	0.87	13.81	3.74
		500	0.24	0.30	1.76	1.48	9.27	1.02	0.16	0.43	0.31	0.67	2.91	1.33
		1000	0.14	0.10	0.89	0.67	19.98	0.53	0.13	0.42	0.48	2.26	2.36	0.93
	60/40	200	0.89	1.56	1.99	3.06	10.81	7.27	0.86	2.21	1.21	1.54	7.04	1.22
		500	0.18	0.27	1.57	0.99	7.31	0.72	0.07	0.21	0.20	0.47	1.41	0.45
		1000	0.05	0.00	0.69	0.65	8.33	0.50	0.01	0.03	0.10	0.32	1.45	0.28
	80/20	200	0.71	2.13	1.58	1.99	5.90	4.89	0.32	0.60	0.74	1.48	1.74	1.58
		500	0.43	0.30	3.35	1.98	5.26	0.55	0.19	0.23	0.34	0.43	1.36	0.45
		1000	0.07	0.04	0.87	0.63	4.31	0.82	0.07	0.12	0.12	0.32	0.66	0.34
Well-Defined, Moderate Thresholds	50/50	200	-0.24	-0.02	4.83	1.34	26.85	2.68	-0.26	-0.02	0.03	0.08	0.96	0.65
		500	-0.35	0.03	4.01	0.69	67.56	2.82	-0.40	-0.11	-0.01	-0.05	0.06	0.05
		1000	-0.39	-0.13	5.30	0.77	48.44	1.08	-0.48	-0.20	-0.03	-0.02	-0.02	0.03
	60/40	200	-0.07	0.02	4.51	1.03	21.74	2.40	-0.14	0.02	0.04	0.10	1.17	0.22
		500	-0.18	-0.05	5.73	0.81	25.99	1.51	-0.23	-0.03	-0.02	-0.05	0.00	0.13
		1000	-0.17	-0.10	4.24	0.56	90.06	1.44	-0.25	-0.08	-0.03	-0.01	-0.01	0.02
	80/20	200	0.15	0.27	9.96	1.91	29.71	5.13	0.11	0.11	0.06	0.11	1.38	1.29
		500	0.17	0.04	8.60	1.14	38.58	2.01	0.04	0.01	-0.01	-0.05	-0.01	0.13
		1000	0.13	0.02	8.16	1.26	47.61	7.20	0.03	-0.04	-0.04	-0.01	-0.01	0.00
Well-Defined, High Thresholds	50/50	200	-0.48	-0.07	10.47	1.01	64.64	14.97	-0.51	-0.07	0.05	0.08	0.74	0.62
		500	-0.48	0.08	24.54	0.74	184.94	19.67	-0.57	-0.13	0.01	-0.03	-0.02	0.02
		1000	-0.36	-0.09	20.26	0.73	136.57	9.26	-0.38	-0.05	-0.04	-0.02	-0.06	0.01
	60/40	200	-0.48	-0.06	12.24	1.10	70.23	12.07	-0.48	-0.05	0.07	0.07	0.48	0.35
		500	-0.51	-0.08	24.12	0.60	165.53	25.89	-0.54	-0.09	0.01	-0.03	-0.07	0.02
		1000	-0.34	-0.07	26.55	1.02	407.56	36.31	-0.39	-0.08	-0.05	-0.03	-0.06	-0.01
	80/20	200	-0.21	0.01	32.04	2.94	131.97	12.49	-0.24	0.00	0.05	0.06	0.21	0.14
		500	-0.40	-0.05	35.28	0.91	107.75	12.60	-0.39	-0.03	0.01	-0.03	-0.11	0.04
		1000	-0.49	-0.09	21.64	0.69	174.59	10.12	-0.46	-0.08	-0.04	-0.03	-0.07	-0.02
Poorly-Defined, Moderate Thresholds	50/50	200	0.67	0.38	0.78	0.48	2.80	1.43	0.47	1.26	0.88	0.64	2.65	1.92
		500	0.38	0.14	1.87	0.50	5.22	1.94	0.50	0.34	0.35	0.25	1.50	1.21
		1000	0.42	0.05	3.94	0.20	9.18	2.15	0.10	0.05	0.07	0.07	0.98	0.49
	60/40	200	5.46	3.15	11.90	2.03	11.64	1.51	4.09	2.05	1.11	8.61	38.94	5.94
		500	1.81	0.32	7.10	3.19	14.31	10.43	0.36	0.42	0.16	0.22	0.89	0.72
		1000	0.32	0.18	2.66	0.94	3.30	6.03	0.06	0.02	0.04	0.10	0.69	0.45
	80/20	200	2.03	1.22	3.30	0.60	7.38	2.50	0.85	0.79	0.80	1.01	2.79	2.42
		500	0.21	0.09	1.63	0.58	2.57	1.41	0.11	0.05	0.06	0.12	0.68	0.44
		1000	0.30	0.11	5.31	0.54	3.19	2.13	0.25	0.17	0.42	0.73	0.60	0.29
Poorly-Defined High Thresholds	50/50	200												
		500												
		1000												
	60/40	200	0.15	-0.45	6736.10	3.41	17497.61	1.34	1.05	1.34	13.58	0.50	1.61	7.61
		500												
	80/20	200	0.12	0.42	68.67	0.28	31.45	2.10	-0.05	0.05	0.36	-0.05	0.92	0.58
		500	-0.15	-0.14	2.51	-0.13	1.11	-0.34	-0.16	-0.05	0.95	0.70	1.12	1.24
		1000	0.21	-0.21	11.79	-0.02	13.84	1.04	0.22	0.15	0.57	-0.16	0.14	-0.14

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. '--' indicates model combinations for which zero valid replications were available to analyze.

Table B.14a. Transition Probability Standard Error Recovery: LMI Pattern A, Ordered Transition Matrix, Four-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Absolute Bias in Estimated Transition Matrix Standard Errors									C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3			
Well-Defined, Low Thresholds	50/50	200	-0.05	0.96	0.00	0.10	0.33	0.05	1.23	0.69	0.71	18.16	20.46	15.44
		500	1.87	0.50	3.34	0.98	0.37	0.25	2.21	1.23	0.26	27.46	22.78	20.43
		1000	0.51	0.21	0.47	1.67	2.58	1.88	3.96	9.64	1.80	11.04	12.22	13.93
	60/40	200	-0.05	-0.06	0.31	-0.16	0.01	-0.07	0.27	0.12	-0.11	0.20	0.72	0.71
		500	0.34	0.48	0.27	0.68	0.51	0.32	1.49	0.95	0.26	3.98	5.35	0.92
		1000	0.62	0.31	0.60	0.68	0.44	0.52	1.14	0.80	0.46	7.47	8.54	10.20
	80/20	200	0.50	0.52	1.17	1.90	0.29	0.69	0.69	9.04	1.87	61.43	65.18	84.78
		500	0.50	0.29	0.49	0.75	0.34	0.33	0.87	1.54	0.95	42.67	41.70	38.89
		1000	0.96	0.38	0.53	1.64	0.83	0.40	4.03	1.12	1.06	35.63	25.20	32.25
Well-Defined, Moderate Thresholds	50/50	200	0.99	0.23	0.68	7.73	1.47	0.73	9.23	2.28	2.68	15.30	19.98	29.19
		500	0.79	0.57	0.56	2.68	0.24	0.06	3.37	0.88	0.36	8.18	14.97	13.21
		1000	0.04	0.03	0.01	1.58	0.08	-0.02	1.03	0.61	0.09	3.86	3.09	5.84
	60/40	200	1.32	0.39	0.53	2.89	3.80	0.12	9.71	1.73	2.17	18.82	30.01	15.28
		500	0.18	0.06	0.06	1.85	0.12	0.01	7.37	1.07	0.68	11.32	13.37	7.36
		1000	0.16	0.18	0.16	8.93	1.02	0.23	12.44	1.15	0.84	3.65	4.21	4.83
	80/20	200	0.87	0.15	0.53	2.41	0.86	0.18	5.81	5.01	5.00	16.88	14.55	25.71
		500	0.17	0.03	0.10	1.28	0.20	0.07	1.07	1.22	2.59	5.69	11.19	19.17
		1000	0.10	0.04	0.05	1.20	0.16	0.03	0.67	1.08	2.50	5.33	7.67	11.75
Well-Defined, High Thresholds	50/50	200	2.98	0.90	0.30	17.38	2.34	0.47	33.95	2.61	1.24	32.44	5.44	17.73
		500	0.63	0.08	0.04	19.77	0.13	0.26	13.11	2.37	0.43	3.37	3.43	3.31
		1000	0.03	0.01	0.03	4.78	0.10	0.01	8.36	1.83	0.17	2.73	4.60	3.01
	60/40	200	2.42	0.23	0.11	25.46	4.24	0.76	101.23	1.71	5.11	7.52	8.01	8.59
		500	0.98	0.09	0.97	9.85	0.48	0.52	23.75	2.90	0.97	8.47	14.14	6.45
		1000	0.37	0.52	0.59	16.20	0.50	0.31	70.84	14.04	0.85	4.24	6.11	2.10
	80/20	200	1.85	0.29	0.71	7.03	1.38	0.26	31.61	3.81	8.65	7.40	2.72	9.26
		500	0.27	-0.01	0.01	0.58	0.07	-0.01	3.04	3.30	2.05	6.73	1.84	2.72
		1000	0.09	0.02	0.04	3.01	0.17	0.03	3.28	3.14	4.03	2.12	3.19	8.20
Poorly-Defined, Moderate Thresholds	50/50	200	2.20	0.04	2.10	4.93	0.33	0.28	5.25	0.19	0.27	24.85	42.81	36.81
		500	1.07	0.61	0.84	1.47	0.43	0.57	0.73	1.41	0.49	26.77	35.62	45.32
		1000	4.77	3.02	1.06	1.55	0.32	32.50	2.14	1.04	0.28	24.13	28.50	26.57
	60/40	200	1.80	0.16	-0.05	1.13	0.21	-0.18	0.30	0.07	-0.07	1.34	1.36	0.06
		500	0.33	0.21	1.15	0.90	0.47	0.19	0.69	0.85	0.52	7.77	4.82	9.38
		1000	1.44	1.36	2.53	1.86	1.01	1.13	0.67	1.46	0.50	0.91	0.65	1.15
	80/20	200	0.33	0.27	0.51	0.72	0.09	0.09	0.27	0.39	0.16	41.61	41.85	43.12
		500	0.45	0.14	0.48	0.83	0.19	0.17	1.26	0.81	1.39	19.76	15.86	15.30
		1000	0.24	0.11	0.24	0.90	0.21	0.25	1.28	0.93	1.02	13.96	24.28	19.51
Poorly-Defined High Thresholds	50/50	200	0.87	1.14	1.98	14.99	1.92	1.68	16.24	0.39	0.86	11.25	21.45	12.54
		500	0.05	0.19	0.32	3.47	1.36	0.33	12.01	1.44	1.04	4.52	7.81	8.13
		1000	0.02	0.02	0.03	2.16	0.24	0.12	5.86	0.72	0.52	4.25	5.37	7.82
	60/40	200	1.18	0.94	2.37	24.65	1.93	2.15	38.71	0.74	1.56	12.97	20.91	14.75
		500	0.10	0.02	0.33	7.43	0.54	0.26	15.72	0.84	0.96	5.77	9.58	8.12
		1000	0.09	0.03	0.08	3.39	0.13	0.10	7.56	0.26	0.44	3.56	12.07	10.50
	80/20	200	1.37	0.45	0.61	5.85	3.85	0.70	9.57	0.94	0.61	6.32	12.73	64.54
		500	0.22	0.13	0.13	2.40	1.18	0.60	8.51	0.92	0.26	1.00	5.02	12.49
		1000	-0.02	-0.01	0.07	0.75	0.26	0.14	2.61	0.81	1.09	0.14	1.19	3.98

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.14b. Transition Probability Standard Error Recovery: LMI Pattern B, Ordered Transition Matrix, Four-Class Solutions

Class Separation Level	Class Prevalence Split	Total Sample Size	Absolute Bias in Estimated Transition Matrix Standard Errors											
			C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4
Well-Defined, Low Thresholds	50/50	200	1.92	0.27	0.16	0.10	5.65	2.22	1.33	2.87	2.01	4.48	3.36	0.66
		500	0.39	0.35	0.96	1.09	0.45	0.68	1.29	0.93	0.56	1.04	0.38	0.99
		1000	0.39	0.20	1.08	1.46	0.44	0.57	2.28	0.74	0.89	0.97	0.52	1.05
	60/40	200	0.16	0.21	0.25	0.24	0.28	0.17	1.32	0.45	0.02	0.13	0.16	0.25
		500	0.54	0.46	3.34	1.79	0.45	2.49	4.54	0.89	0.36	1.96	0.99	0.77
		1000	0.34	0.20	0.81	1.50	0.59	0.37	2.75	0.84	0.85	1.02	0.68	0.64
	80/20	200	0.17	0.43	0.16	-0.13	0.17	0.10	1.00	-0.04	-0.27	0.14	0.05	0.31
		500	0.18	0.21	0.22	1.02	0.36	0.29	1.25	0.35	0.22	0.05	3.82	4.26
		1000	0.55	0.43	0.77	1.13	0.41	0.51	1.42	0.43	0.53	0.41	0.53	0.44
Well-Defined, Moderate Thresholds	50/50	200	1.75	0.62	1.06	7.68	3.17	0.46	49.12	3.83	13.15	8.89	4.32	8.47
		500	0.55	0.09	0.62	4.29	1.98	0.41	24.33	2.40	7.59	3.89	3.85	5.75
		1000	0.22	0.34	0.23	5.17	0.65	0.48	227.15	11.40	30.97	6.30	1.88	4.88
	60/40	200	1.37	0.46	1.29	8.44	2.94	0.44	50.02	3.54	12.49	9.65	3.80	7.40
		500	0.27	0.03	0.21	3.43	0.59	0.06	17.16	1.65	4.50	2.09	3.04	2.74
		1000	0.50	1.23	2.90	3.25	1.86	0.59	23.12	12.12	81.05	8.04	6.88	4.99
	80/20	200	3.23	2.61	2.44	8.95	5.60	0.79	51.16	3.89	9.98	14.70	5.91	12.80
		500	3.92	1.59	3.99	4.55	1.14	0.73	20.36	1.68	7.76	3.99	4.17	5.98
		1000	1.95	1.27	3.71	6.15	1.40	0.40	17.24	3.07	6.84	31.29	5.99	13.93
Well-Defined, High Thresholds	50/50	200	58.26	15.22	49.87	481.27	183.14	22.68	8878.41	46.05	1521.77	333.35	65.81	505.08
		500	6.56	1.13	0.62	321.93	18.04	3.32	1750.30	21.64	230.15	76.13	40.46	110.42
		1000	2.98	0.31	0.21	62.92	5.20	1.01	821.15	18.11	83.91	35.09	31.10	47.50
	60/40	200	74.52	13.14	56.13	437.43	320.96	21.74	8654.01	39.29	1318.00	449.57	504.15	457.65
		500	7.59	1.32	0.56	373.03	25.80	3.55	1900.61	23.42	282.80	85.36	78.37	172.24
		1000	2.32	0.29	0.15	32.71	4.51	1.01	729.79	20.37	83.74	27.40	45.92	51.34
	80/20	200	46.01	11.09	65.73	279.89	188.99	25.35	50339.61	106.50	1066.30	459.30	987.20	299.70
		500	15.76	2.05	2.76	489.38	36.97	4.53	3450.57	26.40	327.22	151.09	66.53	295.98
		1000	6.33	1.66	0.81	52.86	14.09	1.40	1011.17	21.51	208.25	37.41	28.88	64.64
Poorly-Defined, Moderate Thresholds	50/50	200	0.14	0.26	0.26	0.57	0.02	0.01	0.94	3.20	2.16	0.09	0.07	0.01
		500	1.07	0.24	0.78	0.94	0.30	0.37	29.34	15.59	11.61	0.62	0.32	0.58
		1000	0.56	0.21	0.78	1.01	0.15	0.22	3.33	1.15	0.70	0.78	1.17	0.88
	60/40	200	0.38	0.23	0.61	0.61	0.16	0.27	2.37	0.43	0.73	0.23	0.35	0.41
		500	0.76	0.20	1.07	1.52	0.49	0.75	21.00	17.59	9.80	0.36	0.42	1.56
		1000	0.90	0.57	0.88	4.46	0.84	0.44	1.27	0.70	0.80	0.44	0.74	0.70
	80/20	200	-0.06	-0.07	0.06	0.28	-0.03	0.10	0.47	0.12	-0.20	-0.02	-0.14	-0.11
		500	0.38	0.06	0.40	0.37	0.04	0.16	0.30	0.22	-0.07	-0.08	0.02	0.14
		1000	0.76	0.22	0.92	0.59	0.38	0.95	0.62	0.65	1.56	-0.08	0.29	0.12
Poorly-Defined High Thresholds	50/50	200	50.96	10.38	36.32	47.57	14.45	5.02	138.46	9.63	15.13	59.74	14.21	30.81
		500	17.47	6.12	8.69	45.83	16.31	8.52	45.59	15.80	9.71	13.14	11.05	9.44
		1000	1.85	2.01	4.90	24.11	1.76	1.73	27.47	6.73	5.29	6.35	2.63	2.13
	60/40	200	25.28	9.38	21.51	58.68	14.80	4.40	120.97	7.44	10.12	81.96	9.00	33.34
		500	4.45	14.89	23.39	22.06	11.49	10.92	34.85	38.35	4.95	11.91	8.15	7.79
		1000	1.18	1.15	1.94	20.90	1.86	1.52	30.79	5.87	3.31	4.45	2.12	2.43
	80/20	200	44.16	10.32	32.59	51.51	15.99	3.64	127.82	5.00	7.30	121.43	11.95	49.67
		500	3.82	1.95	7.08	42.80	2.17	1.90	36.94	3.77	1.88	25.44	4.26	8.21
		1000	0.96	0.19	1.83	18.45	1.02	0.75	31.96	1.56	2.96	6.89	1.86	2.10

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.14c. Transition Probability Standard Error Recovery: LMI Pattern A, Unordered Transition Matrix, Four-Class Solutions

Absolute Bias in Estimated Transition Matrix Standard Errors														
Class Separation Level	Class Prevalence Split	Total Sample Size	C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4
Well-Defined, Low Thresholds	50/50	200	0.51	0.10	0.32	0.57	0.18	0.34	0.66	0.32	0.00	18.11	11.63	18.26
		500	1.04	0.69	1.17	1.71	1.29	0.99	1.49	1.14	0.66	27.76	24.51	24.04
		1000	0.40	0.31	0.57	1.17	0.60	0.32	0.93	0.70	0.17	17.82	10.48	11.87
	60/40	200	-0.17	0.33	-0.14	0.01	-0.12	-0.28	-0.02	-0.04	0.05	67.11	29.50	13.82
		500	0.34	0.30	-0.06	0.43	0.38	0.47	0.64	0.62	-0.09	11.43	18.85	1.53
		1000	0.21	0.38	1.20	0.45	0.43	0.64	1.65	0.40	0.78	4.24	6.18	5.46
	80/20	200	0.15	0.06	0.40	0.27	0.37	0.23	0.34	0.51	0.27	55.33	70.77	89.04
		500	0.81	0.56	0.50	1.92	0.88	0.42	0.64	0.84	0.76	36.54	36.20	39.73
		1000	0.41	0.20	0.38	0.52	1.06	0.26	0.97	3.05	0.86	27.07	21.94	29.80
Well-Defined, Moderate Thresholds	50/50	200	0.89	0.43	0.54	9.88	5.55	4.04	3.40	0.50	0.83	29.26	81.74	57.72
		500	0.19	0.05	0.32	0.14	0.02	-0.02	0.06	0.13	0.15	3.12	2.82	6.29
		1000	0.01	0.00	0.02	-0.04	0.02	0.00	0.02	0.02	0.06	1.21	1.14	1.58
	60/40	200	0.39	0.19	0.38	0.49	0.41	0.13	0.69	0.22	0.36	15.89	78.41	35.08
		500	0.53	0.36	1.27	0.48	0.13	0.07	0.38	0.35	0.32	6.15	13.26	8.12
		1000	0.04	0.03	0.02	0.02	0.02	-0.01	0.08	0.06	0.09	1.97	2.45	2.04
	80/20	200	1.09	0.17	0.57	0.43	0.61	0.22	0.67	0.68	4.69	24.03	13.05	20.19
		500	0.15	0.00	0.07	0.07	0.10	0.05	0.04	0.10	2.61	6.78	10.59	15.81
		1000	0.02	0.02	0.02	-0.04	0.05	0.03	0.06	0.02	1.81	2.82	2.90	5.08
Well-Defined, High Thresholds	50/50	200	3.16	3.05	5.72	4.06	9.30	3.51	9.17	2.42	2.17	20.21	21.69	34.99
		500	2.33	1.85	1.89	0.98	0.38	0.41	1.27	2.40	2.46	402.59	1249.94	688.83
		1000	41.62	27.80	47.59	25.08	8.89	9.58	3.62	3.60	0.77	61.63	166.43	173.03
	60/40	200	4.47	2.86	3.36	10.64	7.21	2.33	20.86	6.72	41.77	93.17	90.67	147.36
		500	141.25	239.11	196.24	412.89	186.87	209.23	232.22	124.60	27.02	240.21	416.56	236.43
		1000	1.53	1.23	3.97	1.85	0.79	0.93	3.30	1.80	0.98	71.94	126.55	15.35
	80/20	200	1.65	0.29	0.08	0.28	0.90	0.21	-0.02	0.04	4.36	56.14	4.58	64.92
		500	0.61	0.09	0.04	-0.08	0.05	0.07	0.29	0.64	30.60	49.90	85.47	30.16
		1000	0.06	0.01	0.05	-0.09	0.04	0.04	0.02	0.03	5.72	2.90	4.66	4.88
Poorly-Defined, Moderate Thresholds	50/50	200	0.25	0.15	0.40	0.41	0.39	-0.15	0.13	0.50	0.02	25.88	31.66	21.01
		500	0.97	0.75	0.55	10.67	1.45	4.35	0.39	0.86	0.40	16.07	28.96	24.35
		1000	5.39	1.47	2.18	1.42	0.96	0.89	1.45	1.30	1.16	37.92	11.73	10.80
	60/40	200	0.02	0.10	0.15	0.25	0.11	0.09	-0.04	-0.15	-0.32	-0.17	-0.06	-0.17
		500	0.11	-0.11	-0.11	0.06	0.29	0.05	0.08	0.50	-0.27	0.28	1.06	0.55
		1000	18.30	11.72	0.78	129.08	24.57	32.15	1.02	1.88	1.04	2.21	2.74	1.21
	80/20	200	1.25	0.25	1.19	0.55	0.13	-0.03	0.13	0.13	0.37	28.80	24.43	33.04
		500	0.61	0.41	0.54	2.25	0.36	0.58	1.00	0.77	1.32	19.48	26.34	28.66
		1000	1.33	0.47	0.72	0.48	0.15	0.27	0.52	0.46	1.66	13.73	21.65	19.43
Poorly-Defined High Thresholds	50/50	200	1.25	0.77	1.07	1.79	1.79	1.84	0.94	1.63	1.24	17.70	20.63	15.75
		500	0.54	0.98	1.13	0.85	0.73	0.54	1.06	3.85	0.64	30.10	26.43	349.32
		1000	0.29	0.60	0.88	0.50	1.05	0.31	0.83	1.73	0.29	31.33	13.71	51.30
	60/40	200	7.27	6.07	7.13	10.82	1.68	2.02	6.26	2.17	1.84	68.61	50.82	76.40
		500	43.56	45.05	144.66	54.53	246.35	135.79	293.66	2642.82	741.06	14.16	57.14	53.07
		1000	0.19	0.19	0.23	0.12	0.09	0.06	0.23	0.24	0.20	2.44	4.45	3.85
	80/20	200	0.94	0.51	0.77	0.55	1.92	0.71	1.89	0.47	0.69	18.23	22.41	49.38
		500	0.13	0.11	0.21	0.12	1.39	0.77	0.16	1.75	2.47	0.68	3.57	10.34
		1000	-0.01	0.05	0.10	0.06	0.26	0.08	0.18	0.21	0.66	0.65	1.19	4.45

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Table B.14d. Transition Probability Standard Error Recovery: LMI Pattern B, Unordered
Transition Matrix, Four-Class Solutions

			Absolute Bias in Estimated Transition Matrix Standard Errors											
Class Separation Level	Class Prevalence Split	Total Sample Size	C2#1 on C1#1	C2#2 on C1#1	C2#3 on C1#1	C2#1 on C1#2	C2#2 on C1#2	C2#3 on C1#2	C2#1 on C1#3	C2#2 on C1#3	C2#3 on C1#3	C2#1 on C1#4	C2#2 on C1#4	C2#3 on C1#4
Well-Defined, Low Thresholds	50/50	200	0.85	0.12	1.88	0.11	-0.01	0.18	29.14	9.72	13.41	0.99	-0.09	1.17
		500	0.41	0.26	0.86	0.32	0.23	0.54	1.21	0.93	0.69	0.77	0.41	0.68
		1000	0.29	0.18	0.70	0.21	0.23	0.30	0.72	0.47	0.51	0.72	0.49	0.53
	60/40	200	0.25	0.77	0.39	0.23	0.69	0.42	0.61	0.20	-0.19	0.34	0.15	0.30
		500	0.34	0.36	0.67	0.30	0.18	0.43	0.86	0.33	0.26	0.49	0.25	0.44
		1000	0.74	0.49	0.95	0.67	0.57	0.43	1.00	0.92	0.96	1.83	0.91	1.14
	80/20	200	-0.03	0.18	0.73	0.02	0.10	-0.11	-0.04	0.10	-0.16	-0.01	-0.24	0.10
		500	1.36	1.08	1.99	0.27	0.92	0.99	0.54	0.28	0.16	0.11	1.25	0.31
		1000	0.49	0.23	1.52	0.49	0.29	0.50	0.66	0.34	0.63	0.53	0.42	0.46
Well-Defined, Moderate Thresholds	50/50	200	1.28	0.36	1.41	2.76	1.80	0.71	2.70	0.99	6.13	2.14	2.20	5.95
		500	0.19	0.02	0.25	0.08	0.08	0.01	0.39	0.16	0.66	0.60	0.63	0.95
		1000	0.06	0.00	0.12	0.12	0.30	0.09	0.08	0.12	0.85	0.17	0.18	0.36
	60/40	200	1.48	0.29	1.18	0.83	1.68	0.63	1.80	0.93	3.36	2.32	2.28	4.04
		500	0.26	0.04	0.33	0.12	0.09	0.03	0.20	0.18	0.72	0.56	0.69	1.01
		1000	0.06	-0.02	0.16	0.05	0.05	0.09	0.37	0.07	0.51	0.34	0.34	0.60
	80/20	200	1.61	0.58	2.40	0.76	1.42	0.55	1.73	0.71	2.73	12.71	2.58	4.78
		500	3.39	0.89	1.37	0.60	0.46	0.53	1.65	0.22	1.87	1.54	2.06	2.79
		1000	0.12	-0.01	0.09	0.01	0.04	0.04	0.19	0.00	0.27	0.89	0.38	0.80
Well-Defined, High Thresholds	50/50	200	29.27	3.97	15.61	5.32	24.17	3.92	42.46	10.89	106.71	54.92	20.30	139.85
		500	2.80	0.34	0.41	0.64	1.77	0.29	0.48	0.26	5.45	2.08	2.98	6.63
		1000	0.90	0.09	0.61	0.08	0.39	0.07	0.11	0.04	0.97	0.15	0.35	1.54
	60/40	200	49.15	2.64	24.36	13.51	39.91	7.92	22.12	11.14	116.02	105.37	50.98	152.38
		500	6.50	0.95	1.71	4.09	4.99	1.06	3.89	0.55	9.26	5.28	6.66	13.89
		1000	2.05	0.21	0.34	0.35	0.88	0.22	0.27	0.06	1.53	1.26	1.60	3.76
	80/20	200	28.83	4.62	29.96	6.91	26.25	6.40	31.97	4.59	79.62	67.11	68.40	98.15
		500	11.05	1.25	1.31	1.77	4.87	1.38	0.75	0.51	11.49	15.66	17.54	57.75
		1000	1.72	0.13	0.36	0.30	1.03	0.25	0.44	0.06	2.20	2.84	4.20	10.02
Poorly-Defined, Moderate Thresholds	50/50	200	2.87	2.03	0.48	1.65	-0.08	0.02	23.68	11.11	13.96	0.68	0.11	0.31
		500	0.79	0.53	1.28	1.16	0.70	0.54	1.04	1.31	1.26	0.85	0.67	0.87
		1000	0.70	0.29	0.96	0.80	0.12	0.32	0.76	0.89	0.54	0.75	0.61	0.71
	60/40	200	0.43	1.06	2.74	0.38	0.21	0.20	11.59	14.41	13.62	0.16	-0.17	-0.06
		500	0.75	0.23	0.76	0.54	0.57	1.64	1.46	1.63	0.90	0.80	0.35	1.16
		1000	46.48	17.96	1.28	0.80	19.45	1.33	1.70	1.69	0.59	0.58	0.85	0.41
	80/20	200	-0.01	0.04	0.61	0.18	-0.11	-0.10	0.40	0.38	-0.02	0.13	-0.05	0.43
		500	1.31	1.01	2.16	0.20	1.52	1.04	1.68	1.73	1.78	0.95	0.93	1.13
		1000	4.76	10.74	1.55	4.21	1.22	2.71	3.58	2.58	1.72	8.71	1.40	2.58
Poorly-Defined High Thresholds	50/50	200	10.49	7.46	27.49	5.54	9.65	9.90	7.32	9.00	21.35	8.77	5.09	8.10
		500	13.67	2.52	8.40	2.04	2.49	3.04	2.35	3.96	4.48	1.64	3.81	3.92
		1000	18.08	8.00	3.25	2.07	2.83	2.74	5.48	4.20	3.83	52.95	12.06	112.20
	60/40	200	28.59	12.67	38.38	6.25	6.65	9.63	9.60	11.81	15.15	31.40	7.09	12.29
		500	5.14	5.25	11.34	12.13	13.05	10.89	34.77	8.58	30.84	4.71	19.19	18.83
		1000	2.04	0.85	5.62	3.01	1.75	1.90	4.27	3.05	3.36	1.64	2.70	3.14
	80/20	200	16.28	6.41	12.07	7.83	9.18	3.94	10.07	5.57	5.68	68.04	17.23	23.72
		500	4.59	16.49	18.53	32.22	3.40	3.36	4.75	2.44	2.11	5.36	3.66	5.45
		1000	2.46	1.51	6.27	0.94	0.55	0.78	2.32	2.76	3.58	2.69	3.00	4.44

Note. Absolute values of bias less than 0.01 are presented as 0.00 due to rounding. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance.

Appendix C: Programming Examples

Example *Mplus* template used in *MplusAutomation* R package to create individual *Mplus* input files (“LTA_RB1_taus_template.inp”)

```

[[init]]
iterators = classes N gammas taus;
classes = 2:5;
N = 200 500 1000;
gammas = 5050 6040 8020;
taus = 1:2;
filename = "LTA_[[N]]_RB1_[[gammas]]_TB[[taus]]_[[classes]]c.inp";
outputDirectory = C:\Users\ANNA\Desktop\SIMULATION\conditions\working;
[[/init]]

title:      Generate LTA_[[N]]_RB1_[[gammas]]_TB[[taus]]_[[classes]]c
!Pattern = B
!N = [[N]]
!rhos = RB1
!gammas = T2gammas_[[gammas]]
!taus = TB[[taus]]

montecarlo:
    names are u11-u15 u21-u25;
    generate = u11-u15 u21-u25(1);
    categorical = u11-u15 u21-u25;
    genclasses = c1(4) c2(3) ; !generated classes; condition-specific
    classes = c1([[classes]]) c2([[classes]]) ; !estimation model class enumeration
    nob = [[N]]; !sample size; condition-specific
    nrep = 500; !number of replications
    results = LTA_[[N]]_RB1_[[gammas]]_TB[[taus]]_[[classes]]c.csv; !condition-specific

analysis:
    type = mixture;
    parameterization=probability; !Allows transition probabilities
    ! to be expressed directly in terms of probability parameters
    ! instead of via logit parameters.
    mitations = 1000; !#iterations for EM algorithm (default 500)
    starts = 30 4;

!!!!!!!!!!!!!!
!Generating Model!
!!!!!!!!!!!!!!
model population:
    %overall%
    !generated class prevalence proportions (gammas)
    !last class is reference class - no gammas set
[[gammas = 5050]]
    [c1#1*.33];
    [c1#2*.33];
    [c1#3*.17];
[[/gammas = 5050]]

[[gammas = 6040]]
    [c1#1*.33];
    [c1#2*.33];
    [c1#3*.204];
[[/gammas = 6040]]

[[gammas = 8020]]

```

```

[c1#1*.33];
[c1#2*.33];
[c1#3*.272];
[[/gammas = 8020]]

[c2#1*.33];
[c2#2*.33];

!generated transition matrix (taus)
!last class is reference class - no taus set
c2#1 on c1#1*0.85;
c2#2 on c1#1*0.13;

[[taus = 1]]
c2#1 on c1#2*0;
c2#2 on c1#2*0.9;

c2#1 on c1#3*0;
c2#2 on c1#3*0;

c2#1 on c1#4*0;
c2#2 on c1#4*0;
[[/taus = 1]]

[[taus = 2]]
c2#1 on c1#2*0.1;
c2#2 on c1#2*0.8;

c2#1 on c1#3*0.04;
c2#2 on c1#3*0.05;

c2#1 on c1#4*0.03;
c2#2 on c1#4*0.02;
[[/taus = 2]]

!generated logit thresholds for class-specific item response
!probabilities (rhos) - Time 1 Classes
model population-c1:
%c1#1%
[u11$1*1] (1);
[u12$1*1] (2);
[u13$1*1] (3);
[u14$1*1] (4);
[u15$1*1] (5);

%c1#2%
[u11$1*1] (6);
[u12$1*1] (7);
[u13$1*-1] (8);
[u14$1*-1] (9);
[u15$1*-1] (10);

%c1#3%
[u11$1*-1] (11);
[u12$1*-1] (12);
[u13$1*-1] (13);
[u14$1*-1] (14);
[u15$1*-1] (15);

%c1#4%
[u11$1*-1] (16);
[u12$1*-1] (17);
[u13$1*1] (18);
[u14$1*1] (19);
[u15$1*1] (20);

!generated logit thresholds for class-specific item response

```

!probabilities (rhos) - Time 2 Classes

model population-c2:

```

    %c2#1%
    [u21$1*1] (1);
[u22$1*1] (2);
    [u23$1*1] (3);
    [u24$1*1] (4);
[u25$1*1] (5);

```

```

    %c2#2%
    [u21$1*1] (6);
[u22$1*1] (7);
    [u23$1*-1] (8);
    [u24$1*-1] (9);
[u25$1*-1] (10);

```

```

%c2#3%
    [u21$1*-1] (11);
[u22$1*-1] (12);
    [u23$1*-1] (13);
    [u24$1*-1] (14);
[u25$1*-1] (15);

```

!!!!!!!!!!!!!!!

!Estimating Model!

!!!!!!!!!!!!!!!

model:

```

    %overall%
    !transition matrix
c2 on c1;

```

model c1:

```

    %c1#1%
    [u11$1*1] (1);
[u12$1*1] (2);
    [u13$1*1] (3);
    [u14$1*1] (4);
[u15$1*1] (5);

```

```

    %c1#2%
    [u11$1*1] (6);
[u12$1*1] (7);
    [u13$1*-1] (8);
    [u14$1*-1] (9);
[u15$1*-1] (10);

```

```

[[classes > 2]]
    %c1#3%
    [u11$1*-1] (11);
[u12$1*-1] (12);
    [u13$1*-1] (13);
    [u14$1*-1] (14);
[u15$1*-1] (15);
[[/classes > 2]]

```

```

[[classes > 3]]
    %c1#4%
    [u11$1*-1] (16);
[u12$1*-1] (17);
    [u13$1*1] (18);
    [u14$1*1] (19);
[u15$1*1] (20);
[[/classes > 3]]

```

```

[[classes > 4]]

```

```

%c1#5%
    [u1$1] (21);
    [u12$1] (22);
    [u13$1] (23);
    [u14$1] (24);
    [u15$1] (25);
[/classes > 4]]

model c2:
    %c2#1%
    [u21$1*1] (1);
    [u22$1*1] (2);
    [u23$1*1] (3);
    [u24$1*1] (4);
    [u25$1*1] (5);

    %c2#2%
    [u21$1*1] (6);
    [u22$1*1] (7);
    [u23$1*-1] (8);
    [u24$1*-1] (9);
    [u25$1*-1] (10);

[[classes > 2]]
    %c2#3%
    [u21$1*-1] (11);
    [u22$1*-1] (12);
    [u23$1*-1] (13);
    [u24$1*-1] (14);
    [u25$1*-1] (15);
[/classes > 2]]

[[classes > 3]]
    %c2#4%
    [u21$1*-1] (16);
    [u22$1*-1] (17);
    [u23$1*1] (18);
    [u24$1*1] (19);
    [u25$1*1] (20);
[/classes > 3]]

[[classes > 4]]
    %c2#5%
    [u21$1] (21);
    [u22$1] (22);
    [u23$1] (23);
    [u24$1] (24);
    [u25$1] (25);
[/classes > 4]]

output:
    tech1 tech9;

```

Example *Mplus* input file created by the “LTA_RB1_taus_template.inp” template (“LTA_200_RB1_5050_TB1_5c.inp”)

```

title:      Generate LTA_200_RB1_5050_TB1_5c
!Pattern = B
!N = 200
!rhos = RB1
!gammas = T2gammas_5050
!taus = TB1

montecarlo:
  names are u11-u15 u21-u25;
  generate = u11-u15 u21-u25(1);
  categorical = u11-u15 u21-u25;
  genclasses = c1(4) c2(3) ; !generated classes; condition-specific
  classes = c1(5) c2(5) ; !estimation model class enumeration
  nob = 200; !sample size; condition-specific
  nrep = 500; !number of replications
  results = LTA_200_RB1_5050_TB1_5c.csv; !condition-specific

analysis:
  type = mixture;
  parameterization=probability; !Allows transition probabilities
  ! to be expressed directly in terms of probability parameters
  ! instead of via logit parameters.
  mitations = 1000; !#iterations for EM algorithm (default 500)
  starts = 30 4;

!!!!!!!!!!!!!!
!Generating Model!
!!!!!!!!!!!!!!
model population:
  %overall%
  !generated class prevalence proportions (gammas)
  !last class is reference class - no gammas set
  [c1#1*.33];
  [c1#2*.33];
  [c1#3*.17];

  [c2#1*.33];
  [c2#2*.33];

  !generated transition matrix (taus)
  !last class is reference class - no taus set
  c2#1 on c1#1*.85;
  c2#2 on c1#1*.13;

  c2#1 on c1#2*0;
  c2#2 on c1#2*.9;

  c2#1 on c1#3*0;
  c2#2 on c1#3*0;

  c2#1 on c1#4*0;
  c2#2 on c1#4*0;

!generated logit thresholds for class-specific item response
!probabilities (rhos) - Time 1 Classes
model population-c1:
  %c1#1%
  [u11$1*1] (1);
  [u12$1*1] (2);
  [u13$1*1] (3);

```



```

        [u14$1*1] (4);
[u15$1*1] (5);

        %c1#2%
        [u11$1*1] (6);
        [u12$1*1] (7);
        [u13$1*-1] (8);
        [u14$1*-1] (9);
[u15$1*-1] (10);

        %c1#3%
        [u11$1*-1] (11);
        [u12$1*-1] (12);
        [u13$1*-1] (13);
        [u14$1*-1] (14);
[u15$1*-1] (15);

        %c1#4%
        [u11$1*-1] (16);
        [u12$1*-1] (17);
        [u13$1*1] (18);
        [u14$1*1] (19);
[u15$1*1] (20);

!generated logit thresholds for class-specific item response
!probabilities (rhos) - Time 2 Classes
model population-c2:
        %c2#1%
        [u21$1*1] (1);
[u22$1*1] (2);
        [u23$1*1] (3);
        [u24$1*1] (4);
[u25$1*1] (5);

        %c2#2%
        [u21$1*1] (6);
        [u22$1*1] (7);
        [u23$1*-1] (8);
        [u24$1*-1] (9);
[u25$1*-1] (10);

        %c2#3%
        [u21$1*-1] (11);
        [u22$1*-1] (12);
        [u23$1*-1] (13);
        [u24$1*-1] (14);
[u25$1*-1] (15);

!!!!!!!!!!!!!!
!Estimating Model!
!!!!!!!!!!!!!!
model:

        %overall%
        !transition matrix
c2 on c1;

model c1:
        %c1#1%
        [u11$1*1] (1);
        [u12$1*1] (2);
        [u13$1*1] (3);
        [u14$1*1] (4);
        [u15$1*1] (5);

        %c1#2%

```

```

        [u11$1*1] (6);
        [u12$1*1] (7);
        [u13$1*-1] (8);
        [u14$1*-1] (9);
[u15$1*-1] (10);

%c1#3%
        [u11$1*-1] (11);
        [u12$1*-1] (12);
        [u13$1*-1] (13);
        [u14$1*-1] (14);
[u15$1*-1] (15);

%c1#4%
        [u11$1*-1] (16);
        [u12$1*-1] (17);
        [u13$1*1] (18);
        [u14$1*1] (19);
[u15$1*1] (20);

%c1#5%
        [u11$1] (21);
        [u12$1] (22);
        [u13$1] (23);
        [u14$1] (24);
[u15$1] (25);

model c2:
        %c2#1%
        [u21$1*1] (1);
[u22$1*1] (2);
        [u23$1*1] (3);
        [u24$1*1] (4);
[u25$1*1] (5);

        %c2#2%
        [u21$1*1] (6);
        [u22$1*1] (7);
        [u23$1*-1] (8);
        [u24$1*-1] (9);
[u25$1*-1] (10);

        %c2#3%
        [u21$1*-1] (11);
        [u22$1*-1] (12);
        [u23$1*-1] (13);
        [u24$1*-1] (14);
[u25$1*-1] (15);

        %c2#4%
        [u21$1*-1] (16);
        [u22$1*-1] (17);
        [u23$1*1] (18);
        [u24$1*1] (19);
[u25$1*1] (20);

        %c2#5%
        [u21$1] (21);
        [u22$1] (22);
        [u23$1] (23);
        [u24$1] (24);
[u25$1] (25);

output:
        tech1 tech9;

```

Appendix D: Replication-Level Class Enumeration Results

Table D.1. Percent of Converged Replications Yielding k -Class Solutions, AIC

Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Solution			
					2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Low Thresholds	A	Ordered	50/50	200	0.20	52.00	44.20	3.60
				500		1.60	89.40	9.00
				1000		0.20	89.20	10.60
			60/40	200	5.00	77.40	16.20	1.40
				500		61.80	35.00	3.20
				1000		25.60	69.20	5.20
			80/20	200		10.60	77.80	11.60
				500		0.80	89.00	10.20
				1000		0.20	90.00	9.80
		Unordered	50/50	200	2.20	62.60	31.80	3.40
				500		10.60	81.20	8.20
				1000		0.40	90.80	8.80
			60/40	200	10.60	76.00	12.60	0.80
				500	0.20	78.00	19.40	2.40
				1000		66.00	32.00	2.00
			80/20	200	0.20	16.80	73.00	10.00
				500			89.20	10.80
				1000		0.20	90.80	9.00
	B	Ordered	50/50	200	1.80	52.00	42.80	3.40
				500		4.60	83.40	12.00
				1000		0.60	89.80	9.60
			60/40	200	2.00	66.60	29.20	2.20
				500		14.20	77.20	8.60
				1000		0.60	90.60	8.80
		Unordered	80/20	200	4.80	78.80	15.60	0.80
				500		64.60	32.00	3.40
				1000		34.60	59.40	6.00
			50/50	200	2.60	54.40	40.40	2.60
				500		3.20	86.40	10.40
				1000		0.20	92.80	7.00
		60/40	60/40	200	2.60	63.60	31.20	2.60
				500		11.80	81.20	7.00
				1000		0.40	92.60	7.00
		80/20	80/20	200	6.60	76.80	15.80	0.80
				500	0.20	64.60	32.20	3.00
				1000		34.80	60.40	4.80

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Moderate Thresholds	A	Ordered	50/50	200	0.20	4.80	80.00	15.00
				500		1.60	88.80	9.60
				1000		0.40	92.80	6.80
			60/40	200		7.00	82.20	10.80
				500		2.20	87.00	10.80
				1000		1.00	91.00	8.00
			80/20	200	1.40	5.80	76.20	16.60
				500		4.40	86.20	9.40
				1000		0.60	91.40	8.00
		Unordered	50/50	200		4.20	83.00	12.80
				500		1.60	89.80	8.60
				1000		0.60	92.80	6.60
			60/40	200		29.60	65.20	5.20
				500		1.20	91.80	7.00
				1000		0.20	93.00	6.80
			80/20	200	0.60	5.00	79.40	15.00
				500	0.20	1.80	90.80	7.20
				1000		0.80	89.80	9.40
	B	Ordered	50/50	200			95.00	5.00
				500		0.20	95.00	4.80
				1000		0.40	94.00	5.60
			60/40	200		0.20	95.20	4.60
				500		0.20	93.60	6.20
				1000		0.40	92.60	7.00
		Unordered	80/20	200		6.60	89.60	3.80
				500		0.40	94.60	5.00
				1000		0.20	95.80	4.00
			50/50	200			97.00	3.00
				500		0.20	94.00	5.80
				1000		0.20	93.40	6.40
		Unordered	60/40	200			94.60	5.40
				500			94.40	5.60
				1000			93.00	7.00
		Unordered	80/20	200		6.40	88.60	5.00
				500			93.60	6.40
				1000			94.80	5.20

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, High Thresholds	A	Ordered	50/50	200	0.40	21.60	57.80	20.20
				500		7.80	80.40	11.80
				1000		3.60	87.00	9.40
			60/40	200		19.20	58.00	22.80
				500		10.00	79.00	11.00
				1000		3.80	89.40	6.80
			80/20	200	2.80	13.00	64.80	19.40
				500	1.00	7.80	77.60	13.60
				1000	0.60	3.20	83.00	13.20
		Unordered	50/50	200		17.60	62.60	19.80
				500		4.40	84.80	10.80
				1000		1.20	90.40	8.40
			60/40	200		15.00	69.40	15.60
				500		4.80	84.40	10.80
				1000		0.80	91.80	7.40
			80/20	200	0.80	16.00	62.00	21.20
				500	0.40	6.40	81.60	11.60
				1000		3.20	87.40	9.40
	B	Ordered	50/50	200		5.20	88.40	6.40
				500		0.20	99.20	0.60
				1000			98.40	1.60
			60/40	200		6.20	86.40	7.40
				500			99.40	0.60
				1000			98.60	1.40
		Unordered	80/20	200		11.20	75.80	13.00
				500		0.40	98.00	1.60
				1000			97.80	2.20
			50/50	200		0.80	97.20	2.00
				500			96.60	3.40
				1000			96.40	3.60
			60/40	200		2.40	94.00	3.60
				500			97.40	2.60
				1000			95.40	4.60
		80/20		200		9.20	84.60	6.20
				500		0.80	97.40	1.80
				1000			95.80	4.20

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, Moderate Thresholds	A	Ordered	50/50	200	1.60	62.80	34.00	1.60
				500		13.00	79.80	7.20
				1000		0.60	92.20	7.20
			60/40	200	1.20	86.20	12.40	0.20
				500		81.80	16.80	1.40
				1000		64.60	33.20	2.20
			80/20	200		10.40	82.20	7.40
				500			92.60	7.40
				1000			93.80	6.20
		Unordered	50/50	200	1.80	72.40	24.00	1.80
				500		34.60	60.80	4.60
				1000		2.80	89.80	7.40
			60/40	200	1.40	86.00	12.60	
				500		86.80	12.40	0.80
				1000		83.20	16.20	0.60
			80/20	200	0.40	13.00	79.80	6.80
				500		0.20	95.00	4.80
				1000			94.00	6.00
	B	Ordered	50/50	200	1.80	69.00	27.40	1.80
				500		23.60	70.40	6.00
				1000		1.60	88.80	9.60
			60/40	200	1.40	77.60	20.00	1.00
				500		46.20	50.00	3.80
				1000		7.20	86.00	6.80
			80/20	200	1.00	89.60	9.00	0.40
				500		84.60	14.00	1.40
				1000		72.40	26.00	1.60
		Unordered	50/50	200	3.80	69.00	25.20	2.00
				500		23.60	71.40	5.00
				1000		1.40	90.20	8.40
			60/40	200	3.20	76.80	19.20	0.80
				500		47.20	49.20	3.60
				1000		7.80	86.60	5.60
			80/20	200	2.20	84.60	12.60	0.60
				500		82.40	16.00	1.60
				1000		73.60	24.20	2.20

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, High Thresholds	A	Ordered	50/50	200	4.20	11.80	58.60	25.40
				500	1.60	4.40	77.00	17.00
				1000	0.60	2.60	84.00	12.80
			60/40	200	2.00	17.60	58.40	22.00
				500	0.40	7.20	69.60	22.80
				1000	0.20	2.60	85.20	12.00
			80/20	200	2.40	9.60	65.00	23.00
				500	1.20	4.20	82.00	12.60
				1000		3.00	85.80	11.20
		Unordered	50/50	200	2.80	13.80	58.60	24.80
				500	0.80	4.80	76.60	17.80
				1000		1.80	88.80	9.40
			60/40	200	1.60	28.20	54.40	15.80
				500		6.60	75.40	18.00
				1000	0.20	2.60	86.60	10.60
			80/20	200	2.00	9.80	64.80	23.40
				500	1.00	2.00	81.80	15.20
				1000	0.20	2.40	89.20	8.20
	B	Ordered	50/50	200		1.80	92.80	5.40
				500			92.60	7.40
				1000			76.60	23.40
			60/40	200		2.40	94.60	3.00
				500			92.00	8.00
				1000		0.20	79.76	20.04
		Unordered	80/20	200	0.20	7.20	85.20	7.40
				500		0.20	89.00	10.80
				1000			73.20	26.80
			50/50	200		3.00	92.20	4.80
				500		0.20	89.00	10.80
				1000		0.20	77.60	22.20
		60/40	60/40	200		4.20	89.80	6.00
				500		0.20	89.60	10.20
				1000			79.40	20.60
		80/20	80/20	200	0.60	7.40	85.60	6.40
				500		0.20	87.20	12.60
				1000			77.00	23.00

Notes. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Bolded italic cell values reflect percentages greater than or equal to 80%. Rows may not sum to 100% due to rounding.

Table D.2. Percent of Converged Replications Yielding k -Class Solutions, BIC

Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Solution			
					2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Low Thresholds	A	Ordered	50/50	200	87.20	12.80		
				500	8.00	91.20	0.80	
				1000		51.00	48.80	0.20
			60/40	200	97.00	3.00		
				500	34.40	65.60		
				1000	0.20	99.60	0.20	
		80/20		200	55.20	44.60	0.20	
				500		36.20	63.80	
				1000		2.00	94.60	3.40
		Unordered	50/50	200	94.00	6.00		
				500	26.40	73.40	0.20	
				1000		88.00	12.00	
			60/40	200	97.80	2.20		
				500	53.60	46.40		
				1000	1.80	98.00	0.20	
	B	Ordered	80/20	200	68.20	31.60	0.20	
				500	1.40	49.20	49.40	
				1000		2.60	95.40	2.00
		Unordered	50/50	200	89.60	10.40		
				500	21.20	78.40	0.40	
				1000		53.80	46.20	
			60/40	200	93.00	7.00		
				500	25.20	74.80		
				1000	0.20	86.20	13.60	
		Unordered	80/20	200	95.80	4.20		
				500	36.40	63.60		
				1000	2.20	95.40	2.40	
		Unordered	50/50	200	93.20	6.80		
				500	26.40	73.20	0.40	
				1000	0.60	61.40	38.00	
			60/40	200	95.80	4.20		
				500	33.00	66.60	0.40	
				1000	0.20	91.40	8.40	
		80/20		200	98.00	2.00		
				500	49.00	51.00		
				1000	2.40	96.40	1.20	

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Moderate Thresholds	A	Ordered	50/50	200	0.20	11.80	81.20	6.80
				500		1.60	91.60	6.80
				1000		0.40	95.60	4.00
			60/40	200		76.40	23.60	
				500		10.80	87.20	2.00
				1000		1.40	94.00	4.60
			80/20	200	1.40	5.80	77.60	15.20
				500		4.40	88.20	7.40
				1000		0.60	94.80	4.60
		Unordered	50/50	200		18.60	78.80	2.60
				500		1.60	94.00	4.40
				1000		0.60	98.40	1.00
			60/40	200		99.00	1.00	
				500		70.60	29.40	
				1000		11.40	88.40	0.20
			80/20	200	0.60	5.00	80.40	14.00
				500	0.20	1.80	93.40	4.60
				1000		0.80	95.80	3.40
	B	Ordered	50/50	200		2.60	96.80	0.60
				500		0.20	96.40	3.40
				1000		0.40	96.80	2.80
			60/40	200		12.00	87.80	0.20
				500		0.20	96.00	3.80
				1000		0.40	95.60	4.00
		Unordered	80/20	200		84.80	15.20	
				500		11.40	88.60	
				1000		0.20	98.40	1.40
			50/50	200		2.60	97.00	0.40
				500		0.20	98.80	1.00
				1000		0.20	99.60	0.20
		60/40		200		13.20	86.80	
				500			99.20	0.80
				1000			100.00	
		80/20		200		86.00	14.00	
				500		10.80	89.20	
				1000		0.40	99.00	0.60

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, High Thresholds	A	Ordered	50/50	200	0.40	21.60	57.80	20.20
				500		7.80	80.60	11.60
				1000		3.60	88.20	8.20
			60/40	200		34.60	56.60	8.80
				500		10.00	79.60	10.40
				1000		3.80	90.20	6.00
			80/20	200	2.80	13.00	64.80	19.40
				500	1.00	7.80	77.80	13.40
				1000	0.60	3.20	83.80	12.40
		Unordered	50/50	200		17.60	62.60	19.80
				500		4.40	86.40	9.20
				1000		1.20	95.20	3.60
			60/40	200		63.00	36.40	0.60
				500		8.60	85.60	5.80
				1000		0.80	95.80	3.40
			80/20	200	0.80	16.00	62.40	20.80
				500	0.40	6.40	82.60	10.60
				1000		3.20	89.40	7.40
	B	Ordered	50/50	200		5.20	89.00	5.80
				500		0.20	99.80	
				1000			99.60	0.40
			60/40	200		6.20	86.40	7.40
				500			99.80	0.20
				1000			99.60	0.40
		Unordered	80/20	200		27.60	70.00	2.40
				500		0.40	98.80	0.80
				1000			99.60	0.40
			50/50	200		0.80	97.20	2.00
				500			100.00	
				1000			100.00	
			60/40	200		2.40	94.20	3.40
				500			99.80	0.20
				1000			100.00	
		80/20		200		21.20	77.60	1.20
				500		0.80	99.00	0.20
				1000			100.00	

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, Moderate Thresholds	A	Ordered	50/50	200	85.40	14.60		
				500	5.00	95.00		
				1000		95.00	5.00	
			60/40	200	75.20	24.80		
				500	1.60	98.40		
				1000		100.00		
		80/20		200	89.40	10.00	0.60	
				500	2.60	16.80	80.40	0.20
				1000		1.40	96.80	1.80
		Unordered	50/50	200	87.20	12.80		
				500	10.40	89.60		
				1000		99.80	0.20	
			60/40	200	78.60	21.40		
				500	4.20	95.80		
				1000		99.80	0.20	
	B	Ordered	80/20	200	95.00	5.00		
				500	9.00	26.20	64.80	
				1000		1.80	97.20	1.00
			50/50	200	79.40	20.60		
				500	3.40	96.60		
				1000		96.60	3.40	
		Unordered	60/40	200	76.00	24.00		
				500	2.80	97.20		
				1000		99.80	0.20	
			80/20	200	68.20	31.80		
				500	1.20	98.80		
				1000		100.00		
		50/50		200	88.20	11.80		
				500	11.60	88.40		
				1000		97.80	2.20	
		60/40		200	88.00	12.00		
				500	9.20	90.60	0.20	
				1000		99.60	0.40	
		80/20		200	82.40	17.60		
				500	5.60	94.40		
				1000	0.20	99.80		

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, High Thresholds	A	Ordered	50/50	200	5.00	73.40	17.40	4.20
				500	1.60	17.80	76.20	4.40
				1000	0.60	2.80	85.60	11.00
			60/40	200	40.40	56.60	2.80	0.20
				500	1.20	33.00	64.20	1.60
				1000	0.20	4.60	85.80	9.40
			80/20	200	2.40	27.60	64.20	5.80
				500	1.20	4.20	82.20	12.40
				1000		3.00	86.40	10.60
		Unordered	50/50	200	7.00	77.80	12.20	3.00
				500	0.80	22.40	74.80	2.00
				1000		2.40	90.80	6.80
			60/40	200	88.80	11.00	0.20	
				500	12.00	39.20	48.60	0.20
				1000	0.20	5.60	89.00	5.20
			80/20	200	2.00	33.80	58.80	5.40
				500	1.00	2.40	82.60	14.00
				1000	0.20	2.40	91.20	6.20
	B	Ordered	50/50	200		82.20	17.80	
				500		1.00	99.00	
				1000			99.80	0.20
			60/40	200	0.80	87.80	11.40	
				500		3.00	96.80	0.20
				1000		0.20	99.60	0.20
		Unordered	80/20	200	62.20	35.20	2.60	
				500		8.00	92.00	
				1000			99.60	0.40
			50/50	200		89.40	10.60	
				500		3.40	96.60	
				1000		0.20	99.40	0.40
		60/40	60/40	200	1.80	90.00	8.20	
				500		6.40	93.40	0.20
				1000			99.60	0.40
		80/20	80/20	200	67.40	30.20	2.40	
				500		20.60	79.40	
				1000		0.20	99.60	0.20

Notes. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Bolded italic cell values reflect percentages greater than or equal to 80%. Rows may not sum to 100% due to rounding.

Table D.3. Percent of Converged Replications Yielding k -Class Solutions, CAIC

Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	Class Solution			
					2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Low Thresholds	A	Ordered	50/50	200	98.20	1.80		
				500	28.00	72.00		
				1000	0.20	76.60	23.20	
			60/40	200	99.40	0.60		
				500	57.40	42.60		
				1000	0.40	99.40	0.20	
		80/20		200	79.00	21.00		
				500	3.00	64.20	32.80	
				1000		5.00	94.40	0.60
		Unordered	50/50	200	99.00	1.00		
				500	47.20	52.80		
				1000	0.20	96.00	3.80	
			60/40	200	99.60	0.40		
				500	75.80	24.20		
				1000	4.40	95.40	0.20	
	B	Ordered	80/20	200	86.20	13.80		
				500	7.60	71.60	20.80	
				1000		4.60	95.00	0.40
		50/50		200	99.40	0.60		
				500	39.40	60.60		
				1000		76.00	24.00	
		60/40		200	99.40	0.60		
				500	45.60	54.40		
				1000	0.60	95.20	4.20	
		80/20		200	98.80	1.20		
				500	58.20	41.80		
				1000	4.00	95.20	0.80	
	Unordered	50/50		200	99.60	0.40		
				500	49.00	50.80	0.20	
				1000	0.80	81.40	17.80	
		60/40		200	99.60	0.40		
				500	58.20	41.80		
				1000	0.80	96.20	3.00	
		80/20		200	99.60	0.40		
				500	75.00	25.00		
				1000	4.60	94.60	0.80	

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Moderate Thresholds	A	Ordered	50/50	200	0.20	18.40	79.80	1.60
				500		1.60	91.60	6.80
				1000		0.40	95.60	4.00
			60/40	200		89.60	10.40	
				500		17.20	82.00	0.80
				1000		2.40	94.00	3.60
			80/20	200	1.40	6.20	77.60	14.80
				500		4.40	88.20	7.40
				1000		0.60	94.80	4.60
		Unordered	50/50	200		29.00	70.60	0.40
				500		2.00	94.00	4.00
				1000		0.60	98.40	1.00
			60/40	200		99.80	0.20	
				500		86.20	13.80	
				1000		22.60	77.40	
			80/20	200	0.60	5.60	80.40	13.40
				500	0.20	1.80	93.40	4.60
				1000		0.80	95.80	3.40
	B	Ordered	50/50	200		6.40	93.60	
				500		0.20	96.40	3.40
				1000		0.40	96.80	2.80
			60/40	200		26.80	73.20	
				500		0.40	96.00	3.60
				1000		0.40	95.60	4.00
		Unordered	80/20	200		92.60	7.40	
				500		22.20	77.80	
				1000		1.40	98.40	0.20
			50/50	200		5.60	94.20	0.20
				500		0.20	98.80	1.00
				1000		0.20	99.60	0.20
		60/40		200		27.60	72.40	
				500		0.20	99.20	0.60
				1000			100.00	
		80/20		200		93.80	6.20	
				500		25.00	75.00	
				1000		0.60	99.00	0.40

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, High Thresholds	A	Ordered	50/50	200	0.40	21.60	57.80	20.20
				500		7.80	80.60	11.60
				1000		3.60	88.20	8.20
			60/40	200		43.20	54.20	2.60
				500		10.00	79.60	10.40
				1000		3.80	90.20	6.00
		80/20		200	2.80	13.00	64.80	19.40
				500	1.00	7.80	77.80	13.40
				1000	0.60	3.20	83.80	12.40
		Unordered	50/50	200		18.80	62.60	18.60
				500		4.40	86.40	9.20
				1000		1.20	95.20	3.60
			60/40	200		78.80	21.20	
				500		11.60	84.80	3.60
				1000		0.80	95.80	3.40
	B	Ordered	80/20	200	0.80	16.00	62.40	20.80
				500	0.40	6.40	82.60	10.60
				1000		3.20	89.40	7.40
			50/50	200		5.20	89.00	5.80
				500		0.20	99.80	
				1000			99.60	0.40
		Unordered	60/40	200		7.80	86.40	5.80
				500			99.80	0.20
				1000			99.60	0.40
			80/20	200		38.60	60.80	0.60
				500		0.60	98.80	0.60
				1000			99.60	0.40
		50/50		200		0.80	97.20	2.00
				500			100.00	
				1000			100.00	
		60/40		200		3.00	94.20	2.80
				500			99.80	0.20
				1000			100.00	
		80/20		200		32.40	67.40	0.20
				500		0.80	99.00	0.20
				1000			100.00	

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, Moderate Thresholds	A	Ordered	50/50	200	96.60	3.40		
				500	15.40	84.60		
				1000		99.00	1.00	
			60/40	200	91.40	8.60		
				500	8.20	91.80		
				1000		100.00		
		80/20		200	98.00	2.00		
				500	13.40	30.40	56.20	
				1000		2.00	96.80	1.20
		Unordered	50/50	200	97.40	2.60		
				500	22.00	78.00		
				1000		100.00		
			60/40	200	94.40	5.60		
				500	12.80	87.20		
				1000		99.80	0.20	
	B	Ordered	80/20	200	98.60	1.40		
				500	29.60	36.80	33.60	
				1000		3.00	96.80	0.20
		Unordered	50/50	200	92.20	7.80		
				500	10.80	89.20		
				1000		98.80	1.20	
			60/40	200	92.00	8.00		
				500	8.00	92.00		
				1000		100.00		
		Unordered	80/20	200	88.00	12.00		
				500	4.80	95.20		
				1000		100.00		
		Unordered	50/50	200	96.60	3.40		
				500	26.80	73.20		
				1000		100.00		
			60/40	200	96.40	3.60		
				500	22.80	77.20		
				1000	0.20	99.60	0.20	
		80/20		200	94.00	6.00		
				500	16.20	83.80		
				1000	0.20	99.80		

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, High Thresholds	A	Ordered	50/50	200	7.60	81.60	9.20	1.60
				500	1.60	22.20	73.00	3.20
				1000	0.60	4.00	85.60	9.80
			60/40	200	58.60	40.60	0.80	
				500	2.00	42.40	54.60	1.00
				1000	0.20	8.40	85.80	5.60
			80/20	200	2.40	36.60	55.80	5.20
				500	1.20	4.60	82.20	12.00
				1000		3.00	86.40	10.60
		Unordered	50/50	200	10.60	83.60	5.60	0.20
				500	0.80	33.60	63.60	2.00
				1000		4.60	90.80	4.60
			60/40	200	98.20	1.80		
				500	27.40	44.80	27.80	
				1000	0.20	8.40	89.00	2.40
			80/20	200	2.00	43.00	49.60	5.40
				500	1.00	4.00	82.60	12.40
				1000	0.20	2.40	91.20	6.20
		B	50/50	200	0.20	94.60	5.20	
				500		4.20	95.80	
				1000			99.80	0.20
			60/40	200	3.80	92.20	4.00	
				500		8.40	91.60	
				1000		0.20	99.60	0.20
			80/20	200	81.40	18.60		
				500	0.60	24.00	75.40	
				1000			99.60	0.40
		Unordered	50/50	200		97.60	2.40	
				500		11.60	88.40	
				1000		0.20	99.40	0.40
			60/40	200	6.20	92.20	1.60	
				500		21.60	78.40	
				1000			99.60	0.40
			80/20	200	84.40	15.40	0.20	
				500	2.80	41.60	55.60	
				1000		0.40	99.60	

Notes. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Bolded italic cell values reflect percentages greater than or equal to 80%. Rows may not sum to 100% due to rounding.

Table D.4. Percent of Converged Replications Yielding k -Class Solutions, ABIC

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Low Thresholds	A	Ordered	50/50	200	0.80	62.60	35.40	1.20
				500		25.00	74.40	0.60
				1000		1.80	94.20	4.00
			60/40	200	8.20	80.20	10.80	0.80
				500	0.20	95.80	4.00	
				1000		90.40	9.60	
			80/20	200		14.60	75.60	9.80
				500		1.80	93.60	4.60
				1000		0.20	94.60	5.20
		Unordered	50/50	200	3.60	68.80	25.80	1.80
				500		53.60	46.20	0.20
				1000		8.60	91.00	0.40
			60/40	200	14.80	76.60	8.20	0.40
				500	1.20	97.40	1.40	
				1000		97.60	2.40	
			80/20	200	0.20	21.60	72.20	6.00
				500		1.20	93.60	5.20
				1000		0.20	95.40	4.40
	B	Ordered	50/50	200	2.80	60.40	35.20	1.60
				500		28.80	69.60	1.60
				1000		4.20	93.00	2.80
			60/40	200	3.40	74.00	22.00	0.60
				500		57.60	41.80	0.60
				1000		15.40	84.00	0.60
		Unordered	80/20	200	7.80	81.60	10.40	0.20
				500	0.40	94.80	4.80	
				1000	0.20	90.40	9.40	
			50/50	200	3.00	62.40	33.20	1.40
				500		31.60	68.40	
				1000		2.20	97.20	0.60
			60/40	200	5.00	70.40	23.80	0.80
				500		62.00	37.80	0.20
				1000		16.00	83.20	0.80
		80/20		200	11.40	77.60	10.60	0.40
				500	1.00	95.40	3.60	
				1000		91.60	8.20	0.20

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, Moderate Thresholds	A	Ordered	50/50	200	0.20	4.80	80.60	14.40
				500		1.60	91.60	6.80
				1000		0.40	95.60	4.00
			60/40	200		8.20	81.40	10.40
				500		2.20	89.20	8.60
				1000		1.00	94.00	5.00
		Unordered	80/20	200	1.40	5.80	76.80	16.00
				500		4.40	88.20	7.40
				1000		0.60	94.80	4.60
			50/50	200		4.20	84.40	11.40
				500		1.60	94.00	4.40
				1000		0.60	98.40	1.00
	B	Ordered	60/40	200		34.80	61.60	3.60
				500		6.80	91.40	1.80
				1000		0.20	97.60	2.20
			80/20	200	0.60	5.00	79.80	14.60
				500	0.20	1.80	93.40	4.60
				1000		0.80	95.80	3.40
		Unordered	50/50	200			97.00	3.00
				500		0.20	96.40	3.40
				1000		0.40	96.80	2.80
			60/40	200		0.20	96.60	3.20
				500		0.20	96.00	3.80
				1000		0.40	95.60	4.00
		Ordered	80/20	200		9.40	87.80	2.80
				500		0.40	97.00	2.60
				1000		0.20	98.40	1.40
		Unordered	50/50	200			97.80	2.20
				500		0.20	98.80	1.00
				1000		0.20	99.60	0.20
			60/40	200			97.60	2.40
				500			99.20	0.80
				1000			100.00	
		80/20		200		7.60	88.60	3.80
				500			98.80	1.20
				1000			99.00	1.00

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Well-Defined, High Thresholds	A	Ordered	50/50	200	0.40	21.60	57.80	20.20
				500		7.80	80.60	11.60
				1000		3.60	88.20	8.20
			60/40	200		19.20	58.40	22.40
				500		10.00	79.60	10.40
				1000		3.80	90.20	6.00
			80/20	200	2.80	13.00	64.80	19.40
				500	1.00	7.80	77.80	13.40
				1000	0.60	3.20	83.80	12.40
		Unordered	50/50	200		17.60	62.60	19.80
				500		4.40	86.40	9.20
				1000		1.20	95.20	3.60
			60/40	200		15.80	69.40	14.80
				500		4.80	86.00	9.20
				1000		0.80	95.80	3.40
			80/20	200	0.80	16.00	62.00	21.20
				500	0.40	6.40	82.60	10.60
				1000		3.20	89.40	7.40
	B	Ordered	50/50	200		5.20	89.00	5.80
				500		0.20	99.80	
				1000			99.60	0.40
			60/40	200		6.20	86.40	7.40
				500			99.80	0.20
				1000			99.60	0.40
		Unordered	80/20	200		11.20	75.80	13.00
				500		0.40	98.80	0.80
				1000			99.60	0.40
			50/50	200		0.80	97.20	2.00
				500			100.00	
				1000			100.00	
			60/40	200		2.40	94.20	3.40
				500			99.80	0.20
				1000			100.00	
		80/20		200		9.20	84.80	6.00
				500		0.80	99.00	0.20
				1000			100.00	

Continues...

Continued...

					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, Moderate Thresholds	A	Ordered	50/50	200	2.80	69.20	27.20	0.80
				500		64.60	35.40	
				1000		22.60	77.00	
			60/40	200	1.60	89.80	8.60	
				500		99.40	0.60	
				1000		100.00		
		80/20		200	0.60	12.60	81.20	5.60
				500			96.00	4.00
				1000			96.80	3.20
		Unordered	50/50	200	3.60	77.80	17.80	0.80
				500		83.80	16.20	
				1000		57.11	42.89	
			60/40	200	1.80	91.60	6.60	
				500		99.60	0.40	
				1000		99.80	0.20	
		80/20		200	1.80	16.40	77.60	4.20
				500		0.80	97.40	1.80
				1000			97.20	2.80
	B	Ordered	50/50	200	2.00	76.80	20.60	0.60
				500		72.20	27.60	
				1000		30.00	69.40	
			60/40	200	1.80	83.00	15.20	
				500		89.80	10.20	
				1000		69.40	30.60	
		80/20		200	1.00	92.80	6.20	
				500		99.60	0.40	
				1000		99.60	0.40	
		Unordered	50/50	200	5.00	75.60	18.40	1.00
				500		73.40	26.60	
				1000		31.60	68.40	
			60/40	200	3.80	82.60	13.40	0.20
				500		91.40	8.60	
				1000		74.60	25.40	
		80/20		200	3.40	88.20	8.20	0.20
				500		99.60	0.40	
				1000		99.60	0.40	

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					Class Solution			
Class Separation	LMI Pattern	Transition Pattern	Class Prevalence Split	Total Sample Size	2 Classes	3 Classes	4 Classes	5 Classes
Poorly-Defined, High Thresholds	A	Ordered	50/50	200	4.20	14.20	59.00	22.60
				500	1.60	4.40	77.20	16.80
				1000	0.60	2.60	85.60	11.20
			60/40	200	2.00	20.60	57.60	19.80
				500	0.40	7.60	70.40	21.60
				1000	0.20	2.60	85.80	11.40
			80/20	200	2.40	9.60	65.20	22.80
				500	1.20	4.20	82.20	12.40
				1000		3.00	86.40	10.60
		Unordered	50/50	200	2.80	15.80	58.80	22.60
				500	0.80	4.80	79.40	15.00
				1000		1.80	90.80	7.40
			60/40	200	2.20	32.60	51.60	13.60
				500		7.00	77.80	15.20
				1000	0.20	2.60	89.00	8.20
			80/20	200	2.00	9.80	65.80	22.40
				500	1.00	2.00	82.60	14.40
				1000	0.20	2.40	91.20	6.20
	B	Ordered	50/50	200		2.80	93.60	3.60
				500			99.40	0.60
				1000			99.80	0.20
			60/40	200		3.20	95.00	1.80
				500			99.00	1.00
				1000		0.20	99.60	0.20
		Unordered	80/20	200	0.20	10.20	85.00	4.60
				500		0.20	99.00	0.80
				1000			99.40	0.60
			50/50	200		3.80	93.80	2.40
				500		0.20	99.40	0.40
				1000		0.20	99.40	0.40
		60/40	60/40	200		5.00	91.00	4.00
				500		0.20	99.20	0.60
				1000			99.60	0.40
		80/20	80/20	200	0.80	8.60	85.20	5.40
				500		0.40	98.60	1.00
				1000			99.60	0.40

Notes. Color gradient is only a visual depiction of the range of values within the table, and not indicative of statistical significance. Bolded italic cell values reflect percentages greater than or equal to 80%. Rows may not sum to 100% due to rounding.

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